Assessing the Costs of Balancing College and Work Activities: The Gig Economy Meets Online Education*

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Abstract

Balancing the demands of work and schooling is a challenging task for an increasing number of students who have to pay their way through college and for workers who intend to upgrade their skills. However, flexible learning and working environments could play an important role in easing many frictions associated with performing both activities simultaneously. Using detailed data from gig workers enrolled in online college education, we analyze how labor supply and study efforts respond to changes in labor market conditions and college activities/tasks. Our findings indicate that average weekly college activities reduce weekly time spent on the Uber platform by 1.7 hours, representing a "short run" opportunity cost of only $41 per week. We also show that study time is not particularly sensitive to changes in labor market conditions, where a 10% increase in average weekly pay reduces study hours by only 2%. Consistent with these results, we find that workers take advantage of their flexible schedules by changing their usual working hours when college activities are more demanding. Finally, we do not find adverse effects of work hours on academic performance in this context, or of study hours on workplace performance (as measured by driver ratings or tips). Overall, the evidence suggests that combining flexible working and learning formats could constitute a suitable path for many (low-SES) students who work to afford an increasingly expensive college education and for workers aiming to improve their skill set.

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1 Introduction

In 2019, 45% of full-time and 84% of part-time undergraduate students in the United States worked for pay (US Department of Education, 2020). The vast majority of these students—64% (86%) of undergraduate students enrolled full-time (part-time)—worked at least 20 hours per week. In addition, the share of students working while attending higher education has been rising over time: the average labor supply among 18 to 22-year-old full-time undergraduates nearly doubled between 1970 and 2000 (Scott-Clayton, 2012).[1] This tendency is likely to continue for two key reasons. First, the cost of a college education has drastically risen over recent decades, forcing many students to work to pay their way through college.[2] Second, the acceleration of technological change has substantially decreased the demand for low-skill/routine labor, driving many workers to upgrade their skills by re-enrolling in post-secondary education programs while working either full- or part-time (Saliola et al., 2020).

At the same time, existing evidence suggests that employment during college meaningfully crowds out schooling time, generally (though not always) negatively affecting college outcomes (Stinebrickner and Stinebrickner, 2003; Beffy et al., 2010; Kalenkoski and Pabilonia, 2010; Scott-Clayton, 2012; Darolia, 2014; Neyt et al., 2019; Le Barbanchon et al., 2020). Taken together, these facts highlight the potential value of exploring new alternatives/policies that could help students balance both activities.

In this study, we aim to highlight the role of adopting and integrating flexible learning and working modalities in mitigating the obstacles students typically face when combining employment with college education (e.g., commuting time and scheduling conflicts). Moreover, the fact that the trend toward online classes and flexible work schedules is expected to grow, driven both by the expanding gig economy—as evidenced by the 8% growth in freelance

[1] The share of students working in college has increased by approximately 10% since 2010 (US Department of Education, 2020).

[2] Between 2006 and 2020, after adjusting for inflation, the average attendance cost at public and non-profit private four-year universities increased by almost 20%. However, average net prices increased more steadily during this period (Ma and Pender, 2022).

workers from 2014 to 2019—and by the increasing number of online learners—highlighted by the rise from 28% of students in post-secondary institutions taking distance courses in 2014 to 37% in 2019—makes the analysis of this environment even more relevant.[3] Furthermore, if we consider that students from lower socioeconomic strata are more prone to working while in college (Chen and Nunnery, 2019), evaluating the potential impacts of flexible formats on leveling the playing field in higher education is of first-order importance if we intend to reduce educational disparities across socioeconomic groups. The purpose of this study is to estimate key cross-elasticities that quantify the tradeoffs associated with performing both activities in a highly flexible context (i.e., online learning while working flexible hours).[4] To our knowledge, this is the first paper quantifying the interdependence of college and work demands. While many studies have focused on the effect of work on schooling performance, to date, there is no evidence of the causal impact of college activities on labor supply or the effects of earnings on the effort exerted in college classes.

Uncovering these elasticities is often complex and, in many cases, intractable due to data limitations and/or problems of selection and endogeneity. To overcome these challenges, we focus on a partnership between Arizona State University (ASU) and Uber, which allows eligible drivers to enroll in online classes at ASU tuition-free; henceforth, we refer to the drivers enrolled in the ASU program as Uber-students. This setting is unique for three reasons. First, Uber-students face a uniquely flexible environment where work and study hours can be easily accommodated.[5] This allows us to determine whether the usual frictions that arise from balancing work and learning still play an important role in this context. Second, Uber and ASU online platforms provide granular and high-frequency information about drivers and students over time, offering a unique opportunity to explore how effort responds

[3]Source: Statista, 2022 and U.S. Department of Education, National Center for Education Statistics. Digest of Education Statistics 2020, Table 311.15.

[4]Estimating these elasticities can also be relevant to inform other settings. For example, if working college students have to substantially decrease their labor supply to complete their studies (high opportunity cost in the short-run), even in a very flexible context, then the scope for many individuals to successfully perform both activities simultaneously is likely limited.

[5]ASU Online classes allow for asynchronous learning, meaning coursework can be completed at any time in alignment with the student's schedule.

to changes in work and college conditions. Third, the degree of complementarity between working activities in this setting and the skills acquired in college is expected to be much lower than in other contexts, making the interpretation of our findings more transparent.

This partnership provides us with two unique datasets that we combine for our analysis. The first, provided by Uber, includes information on drivers enrolled in online BA degree-seeking programs at ASU and a subset of their co-workers who qualified for but did not enroll in the ASU program. The second source of data, provided by ASU, includes academic information on the universe of Uber-students and their online classmates who do not drive with Uber. In particular, we have access to most of the student and driver weekly activity recorded on the Uber and ASU online platforms. The ASU-related information includes student background characteristics, transcript data, and weekly level information collected from their online activity (i.e., points earned, assignments submitted, logins, clicks, and minutes online). Finally, the Uber-related data include weekly information on completed trips, total pay, minutes on the application, driving habits, city-level labor market conditions, and background characteristics, among other covariates.

Our econometric specifications are derived from a simple analytical framework that not only provides justification to our empirical models but also helps to further characterize the cost of performing learning and working activities simultaneously. To overcome common problems of selection and endogeneity, our empirical strategy exploits within-individual and classroom-level variation jointly with instrumental variables to identify the costs associated with balancing work and learning activities. More specifically, we exploit weekly-level variation in the Uber and ASU platforms and (arguably) exogenous changes in labor market demand and course-week learning tasks (i.e., course demand) to identify key cross-elasticities.[6] Finally, the fact that our empirical approach relies on individual-level variation within a short span period (academic terms) allows us to overcome concerns related to whether (if any) previous disengagement from school or work can be driving our main results.

[6]Given that our data come from drivers in a large number of cities, changes in labor demand could be driven, for example, by different social events that may happen in these cities.

Our main findings indicate that average weekly course demand decreases weekly driving time by approximately 1.7 hours: more specifically, a 10% increase in average online learning activities decreases average driving time by approximately 1%.[7] This implies a decrease in Uber-students' incomes of $41 per week or $180 per month, suggesting that the "short-run" opportunity cost (in terms of current income) of online classes is quite low.[8] We also find that a 10% increase in market-level hourly pay only decreases study time for the average Uber-student by approximately 2%, indicating that study time is relatively insensitive to labor market conditions. Overall, these cross-elasticities signal little crowd-out between school and labor market activities in this setting.

Consistent with these findings, we also show that drivers take advantage of the flexibility specific to this context by adjusting their driving patterns when college activities become more demanding. This behavior likely limits the scope of crowd-out. It is worth noting that we see no meaningful effect of college activities on the quality of work (as measured by the impact on driver ratings or tips). In a similar vein, we do not find that driving hours have a negative impact on academic performance. This last result contrasts with the findings of Stinebrickner and Stinebrickner (2003), where an additional hour of work in a very different context of in-person classes has a large and statistically significant negative impact on grades.

Taken together, our results are quite reassuring. They strongly indicate that flexibility in learning and working environments eases many of the frictions associated with performing these activities simultaneously, providing a suitable path for many (low-income or low-socioeconomic background) students who work to pay their way through an increasingly expensive college education. Finally, our findings also suggest that combining flexible work and learning formats constitutes a promising avenue for allowing workers to up-skill without incurring significant short-term costs.

The rest of this study is organized as follows. Section 2 describes the institutional de-

[7]Henceforth, driving time refers to the number of hours that drivers spend connected to the Uber platform.

[8]As a point of comparison, the average Uber-student receives a tuition subsidy of approximately $4,500 per term and earns $2,200 per month when not taking ASU classes.

tails concerning the ASU-Uber partnership, while Section 3 describes the data. Section 4 presents a simple analytical framework. Section 5 describes the empirical strategy. Section 6 quantifies key trade-offs associated with working while attending college. Section 7 further characterizes the cost of performing working and learning activities simultaneously. Section 8 discusses the role of flexibility. Section 9 shows how effort measures impact academic performance. Finally, Section 10 concludes.

2 Institutional Details: The ASU-Uber Partnership

Beginning in the fall semester of 2018, ASU and Uber initiated a partnership to make higher education more accessible to drivers who consistently use the Uber application. This partnership established that Uber will cover the tuition of drivers anywhere in the US who have completed at least 3,000 rides and maintain an Uber Pro Gold, Platinum, or Diamond status.[9] With the guarantee of tuition coverage, participants have several options to choose from in furthering their education. The first and most relevant for this paper is the option to earn credits toward an undergraduate degree. Alternatively, participants may take non-degree enrichment entrepreneurship or English language competency courses (though we do not focus on these short programs). These alternatives provide a lower commitment option to drivers who want to invest in their skills but do not want to commit to a degree program. Qualifying Uber participants pursuing an undergraduate degree at ASU have over 140 degree programs to choose from. Though the degrees are all through the ASU's Online program, ASU does not distinguish between in-person and online degrees on a student's transcript or diploma. Thus, the ASU-Uber partnership provides an interesting option for many drivers that use the Uber application.

While the qualifying restriction of completing at least 3,000 rides might appear quite

[9]The status is determined by the average star rating that drivers receive from passengers and by their trip cancellation rate. The program also extends to beneficiaries of the drivers, such as a spouse, child, sibling, or parent. However, our analysis focuses only on drivers. Approximately 30% of the program participants are family members of the Uber drivers.

daunting, this number is attainable for many drivers, even for those working part-time. For example, the Uber-students in our sample complete an average of roughly 43 trips per week when they are not actively enrolled in classes. At that rate, drivers would surpass the necessary 3,000 trips in less than a year and a half, and even a more casual driver that completes only 30 trips per week would surpass the qualification in under two years.[10] Once this goal is met, drivers must also have reached either Uber Pro Gold, Platinum, or Diamond. To first achieve Gold status, a driver must meet a location-specific point goal, have an average star rating of 4.85 or greater, and have a cancellation rate (conditional on trip acceptance) of under 4 percent.[11] Once one of these different Uber statuses has been attained, the driver must continue to reach their location specific point total, receive a minimum star rating of 4.75, and maintain a cancellation rate below 10 percent in order to keep their Uber Pro status. The Uber Pro Gold, Platinum, or Diamond status must be held in three-month periods, such that the activity in the previous three months determines the status in the current period.[12]

3 Data Description

Our analysis relies on two novel data sources. The first, provided by Arizona State University, allows us to track how Uber-students and their class peers interact with each course's online platform at a weekly frequency and how they perform in their courses on weekly assignments and overall. The second set of data comes from Uber. It includes the universe of drivers participating in the ASU-Uber partnership (i.e., excludes family members) and a subset of

[10]As of May 2023, the threshold was adjusted to 2,000 trips, though we do not have data for this period.

[11]The specific particulars of the point-based goals depend on location, but we can provide some general insights. These points are earned through the completion of rides, with the number of points awarded per completed trip being one or more, contingent upon the time of day and other factors. In most areas (with some exceptions), drivers must accrue between 200 and 600 points within a three-month timeframe to sustain their status. As an illustrative example, assuming a midpoint target of 400 points and 1.5 points per trip, our rough calculations suggest that drivers would need to complete less than 21 trips each week to meet this goal.

[12]The following link https://uber.asu.edu/ provides further details concerning the program's characteristics.

all the qualifying drivers for the ASU-Uber program that chose not to enroll. It is worth noting that the data include student-drivers from across the country (i.e., the sample is not circumscribed to students living in Arizona). We merged these databases at the individual-week level. Finally, we also have access to information on market-level demand in each driver's local labor market.

We exclude the peak of the COVID-19 outbreak period from the analysis since the pandemic substantially disrupted drivers' Uber activities. Thus, we limit our analysis to August 2018 through March 2020, and August 2021 through December 2021.[13] The following subsections present summary statistics and highlight several key features of each data set. Appendix A specifies how the final sample was constructed.

3.1 ASU Data

The first data set we employ in our analysis comes from students enrolled in online undergraduate programs at ASU. Since the degree programs available to drivers in the ASU-Uber partnership are all operated through ASU Online, the students primarily interact with the course and materials through Canvas, an online learning management system. This program feature allows us to access students' background characteristics and track each student's activity in a given course every week. This data set includes many measures of activity on Canvas at the student-class level, such as the number of days online, number of Canvas logins, total clicks, and total minutes online during the week. In addition, we have information on each student's weekly achievement (e.g., total points earned, total points possible, assignments submitted, and assignments graded), their final course grades, field of study, and other background characteristics.

[13] Our main results are qualitatively similar if we restrict the analysis to the pre-COVID-19 period only.

Table 1: Student level observables, by sample

	Uber-Students		Class Peers		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Background Characteristics					
Age	39.25	(10.029)	24.90	(7.491)	14.36***
Female	0.15	(0.361)	0.56	(0.496)	-0.41***
White	0.36	(0.480)	0.54	(0.498)	-0.18***
Black	0.33	(0.470)	0.06	(0.240)	0.27***
Hispanic	0.15	(0.353)	0.23	(0.420)	-0.08***
Asian	0.07	(0.251)	0.08	(0.275)	-0.01**
First generation	0.57	(0.495)	0.36	(0.479)	0.21***
AZ resident	0.06	(0.238)	0.52	(0.500)	-0.46***
Financial need					
None	0.01	(0.072)	0.02	(0.155)	-0.02***
Very low	0.03	(0.170)	0.08	(0.278)	-0.05***
Low	0.08	(0.269)	0.11	(0.309)	-0.03***
Moderate	0.24	(0.427)	0.20	(0.400)	0.04***
High	0.16	(0.366)	0.15	(0.354)	0.01
Very high	0.49	(0.500)	0.38	(0.486)	0.10***
Ever Pell eligible	0.50	(0.500)	0.44	(0.497)	0.06***
Academic Profile					
Incoming GPA	2.71	(0.587)	3.09	(0.621)	-0.38***
Transfer status	0.62	(0.486)	0.51	(0.500)	0.11***
Transfer credit hours	73.19	(51.549)	38.93	(39.006)	34.24***
Number of terms enrolled	3.01	(1.656)	4.64	(3.280)	-1.63***
Average credit hour load	7.95	(3.027)	8.77	(3.147)	-0.82***
STEM degree	0.40	(0.489)	0.30	(0.456)	0.10***
Observations	1540		141913		

Note: Weekly Canvas activity. "Uber-students" refers to ASU students participating in the ASU-Uber partnership. "Class peers" corresponds to students enrolled in the same classes as the Uber students. First-generation refers to students whose parents did not attend college. "AZ resident" indicates if the student is listed as an Arizona resident. Each of the financial need variables "None", "Very low", "Low", "Moderate", "High", and "Very high" indicate the financial need status of the student which is constructed by ASU based on students' applications to federal student aid. "Ever Pell eligible" indicates if the student was ever eligible for a Pell grant. The variable incoming GPA corresponds to a student's transfer GPA or, if transfer GPA is inapplicable, high school GPA. "Transfer status" is an indicator variable denoting whether the student transferred from another higher-education institution, and "transfer credit hours" refer to the number of credit hours carried over from their previous institution. "Number of terms enrolled" denotes the number of distinct terms that the student has been enrolled in ASU courses. "Average credit hour load" reflects the student's average number of credit hours per term and "STEM degree" indicates if the student is in a science, technology, engineering, or math degree program. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

3.1.1 Characterizing ASU-Uber Students

Background Characteristics Table 1 shows background characteristics and proxies for academic preparation of Uber-students and their classmates enrolled in ASU-Online undergraduate programs. More specifically, column (1) corresponds to Uber-students, while column (2) focuses on their classmates that do not work with Uber. Uber-students differ in multiple dimensions from their classmates. They are, on average, 14 years older, overwhelmingly male (85%), and more racially diverse. For instance, 33% of the Uber-students are black, whereas the analogous share for their peer population is only 6%. In addition, Uber-students are more likely to be first-generation (i.e., do not have a parent who graduated from college) and to reside outside Arizona. The middle panel shows that Uber-students have higher financial needs (based on FAFSA records): 49% of them are designated as "very high" financial need versus 38% of their peers; they are also more likely to be eligible for Pell Grants. The last panel shows that Uber-students have lower high school/incoming GPAs than their counterparts, are more likely to transfer from other institutions, were enrolled in fewer terms at ASU (because the partnership is relatively new), are more likely to pursue a major in STEM, and have a lower average course credit hour load per term than their class peers.[14] In summary, the main takeaway from Table 1 is that the ASU-Uber program seems to attract individuals more likely to be racial minorities and disadvantaged.

Weekly Academic Engagement Table 2 shows weekly level proxy measures for student engagement (i.e., active days, clicks, hours online) and performance in ASU online courses. The sample is divided into three groups: Uber-students active in Uber, Uber-students inactive in Uber, and class peers, where active and inactive distinguish the weeks in which Uber-students were actively participating on the Uber platform; if they complete at least

[14] The five most popular majors among the Uber-students are information technology, business, liberal studies, software engineering, and psychology. According to the information provided by the College Scorecard (U.S. Department of Education), the median earnings of Arizona State University graduates four years after graduation are $70,685 for business, $101,600 for computer engineering, and $45,403 for psychology majors. There is no available information for the other two majors.

Table 2: Weekly Canvas activity and outcomes, by sample

	(1)		(2)		(3)		(4)	(5)
	Uber-Students Active in Uber		Uber-Students Inactive in Uber		Class Peers		Col (1) - (3)	Col (1) - (2)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Difference	Difference
Activity								
Days connected to Canvas per course	3.57	(2.30)	3.75	(2.27)	3.48	(2.12)	0.09***	-0.18***
Clicks per course	75.97	(89.33)	79.04	(85.57)	63.94	(69.70)	12.03***	-3.07***
Hours online per course	1.57	(2.12)	1.61	(2.10)	1.25	(1.64)	0.31***	-0.04**
Outcomes								
Assignments submitted per course	1.97	(4.14)	1.99	(2.92)	2.12	(4.05)	-0.15***	-0.02
Assignment share per course (%)	90.19	(27.59)	90.55	(26.81)	91.56	(25.10)	-1.37***	-0.36
Point share per course (%)	79.40	(29.31)	80.13	(28.66)	81.16	(28.64)	-1.76***	-0.74**
Observations	43527		12201		1831331			

Note: All statistics reported in the table are at the weekly level. "Uber-Students: Active in Uber" denotes weeks in which the student shows positive driving hours and is enrolled in ASU classes. "Uber Students: Inactive in Uber" denotes weeks in which the student shows zero driving hours but is enrolled in ASU classes. "Class peers" correspond to students who are enrolled in the same classes as the Uber students. Assignment and point shares refer to the total number of assignments submitted and points earned relative to the number of assignments due and points possible, respectively. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

one trip during a week, they are classified as active. On average, Uber-students show a higher engagement on Canvas than their classmates. They tend to spend more days per week connected to the ASU platform, perform more clicks, and spend more time on the platform.[15] Interestingly, Uber-students also slightly increase their engagement on Canvas during weeks when they are inactive on the Uber platform. Finally, students spend 1.6 hours online per course in a given week, making a total of 2.84 hours of online study activity per week when averaging across all courses and weeks.

In terms of weekly academic performance, Uber-students submit, on average, 1.97 assignments per course during active driving weeks, slightly less than their peers (2.12), representing 90.2% of the total assignments requested. They obtain approximately 80% of the total points, which is similar to the point share of their class peers (81%); differences in weekly academic performance between active and inactive Uber weeks are small.[16] To conclude, a possible concern with these data is that our various Canvas engagement variables may be

[15] Appendix Table A1 shows that our measures of online activity (i.e., days connected to Canvas, number of logins and clicks, and time spent on the platform) are highly correlated. In particular, the high correlation between hours online and clicks suggests that idle time is not likely to be an important concern when proxying study time with "hours online".

[16] The point share is determined by dividing the points earned in a course for a given week by the points possible for the student in a given course-week. Assignments submitted refer to the number of assignments the student submitted throughout the week (assignments do not necessarily need to be submitted in the week they are due).

Table 3: Course-level summary statistics, by sample

	(1)		(2)		(3)
	Uber Students		Class Peers		Col (1) - (2)
	Mean	Std. Dev.	Mean	Std. Dev.	Difference
Activity					
Total hours on Canvas	14.63	(12.73)	11.47	(9.62)	3.16***
Assignments submitted	18.38	(16.89)	19.37	(17.54)	-0.10***
Outcomes					
Passed course	0.76	(0.43)	0.83	(0.38)	-0.07***
Numeric course grade	2.49	(1.66)	2.70	(1.54)	-0.21***
Observations	6591		213842		

Note: "Uber-Students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

incomplete measures of study time and effort. For example, time spent reading hard copies of a textbook would not be included in the measure of minutes on Canvas. However, the strong correlation between Canvas hours and academic performance that we show in Section 9 suggests that our measures of study effort constitute good proxies for actual study time.[17]

In Appendix Table A2, we provide another version of Table 2 where we re-weight the control group by coarsened exact matching (see Iacus et al., 2012) on many of the observable characteristics presented in Table 1. After doing so, the Uber-students' Canvas activity measures are much more similar to the control group, suggesting that once we control for fixed observable characteristics the Uber-students study behaviors are quite similar to their non-Uber peers.

Course-Level Academic Outcomes Table 3 shows course-level information corresponding to Uber-students and their class peers. The top panel presents summary statistics on course-level activity, and the bottom panel displays information on course academic outcomes. On average, Uber-students stay connected to Canvas fourteen hours per course

[17]Furthermore, under the assumption that the ratio of the study time allocated within and outside the ASU online platforms remains fairly stable across various weeks, then our empirical methodology, which includes individual fixed effects, could (partially) address this measurement issue.

(including drop-outs), where most courses last approximately seven to eight weeks.[18] This is roughly 3.2 hours more than their peers. Uber-students also submit a similar number of assignments throughout the course as their peers. Specifically, they submit roughly 18.4 assignments per course, whereas their classmates submit approximately 19.4. These numbers suggest that the course-level activity of Uber students is also similar to those of their peers when considering overall course-level information.

The bottom panel shows that Uber-students have a 76% passing rate and average course grades of 2.49.[19] Unlike activity, these measures of academic performance are somewhat worse compared to their peers (i.e., a passing rate of 83% and an average grade of 2.70).[20] However, these differences are somewhat expected given that enrolled Uber-students, on average, are from less advantaged backgrounds and have substantially lower prior academic credentials. In light of the evidence presented in this table, the higher levels of engagement presented in Table 2 could be interpreted as Uber-students exerting more effort to catch up with the course material.

Overall, the main takeaway from these summary statistics is that Uber-students, despite coming from more disadvantaged backgrounds than their class peers, have only slightly lower course completion rates and grades but somewhat higher levels of engagement in learning activities than their classmates.

3.1.2 Event Study of Weekly Canvas Engagement

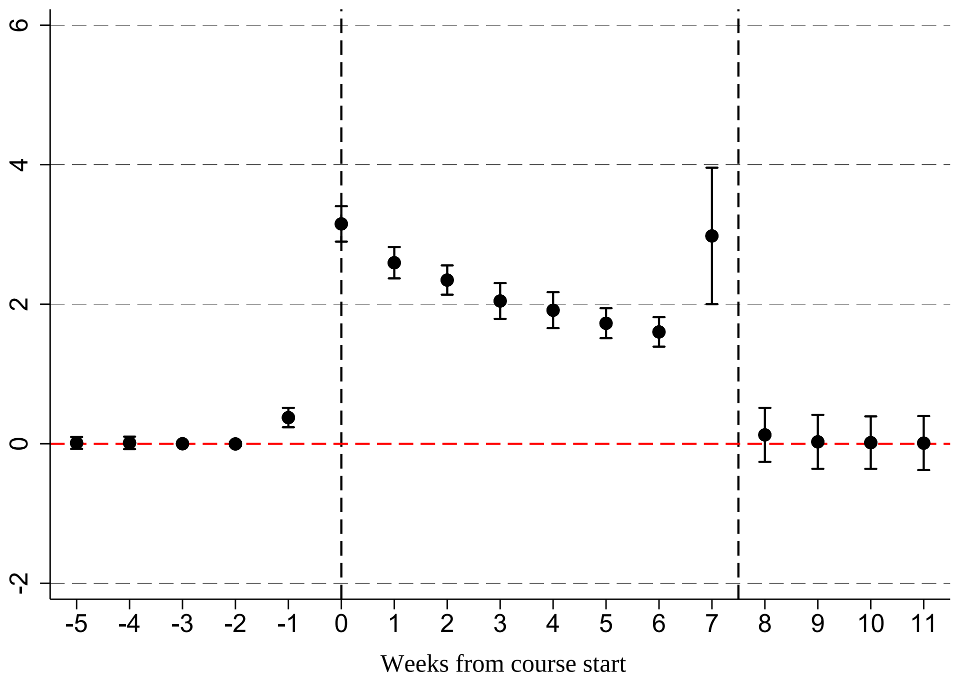
To further characterize the variation in weekly course effort, we perform an event study analysis that focuses on Uber-student Canvas hours. In particular, we analyze how study

[18] A small number of courses are 15-16 weeks long.

[19] The average course pass rate of the Uber-students in their top 10 most popular classes is also very similar to those observed for in-person students in those same classes. If dropping out is defined as not being enrolled for two consecutive terms, we find that 29% of the Uber-students have left the program, while for in-person students, according to ASU facts (https/facts.asu.edu), the first-year retention rate is 86% (for full-time students), and the 4-year (6-year) graduation rate is 55.4% (67.6%).

[20] Appendix Table A3 also presents summary statistics regarding the progress of Uber-students and their class peers (i.e., cumulative GPA, and credits to date). Additionally, Appendix Table A4 presents the same summary statistics as in Table 3, but when we re-weight the "Class Peers" to be more similar to the Uber-students on observables. Once re-weighting, the differences in activity across groups attenuate considerably.

Figure 1: Event study results for study time during eight weeks courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is hours on Canvas and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

time in the different weeks of the term compares to the third week before the beginning of the academic semester.[21] The results corresponding to eight-week-long courses (which is the

[21] We estimate a specification of the following form:

$$CourseE_{i,c,t} = \sum_{\substack{y=-5 \\ y\neq -3}}^{T} \alpha_t \mathbb{I}(t-t^*=y) + \beta_1 \sum CourseWork_{i,t,-c} + \beta_2 MarketHourlyPay_{l,t} + \beta_3 Weather_{l,t} + X_{i,t}\Phi + \psi_i + \delta_m + \phi_c + \varepsilon_{i,t}, \tag{1}$$

where $CourseE_{i,c,t}$ is Canvas hours for Uber-student i, taking course c, in week t. $CourseWork_{i,t,-c}$ captures course peer activities in the other courses ($-c$) in which the student is enrolled (controlling or not for this variable provides very similar results). The vector $X_{i,t}$ includes controls for the number of course days in the week and if the week includes Christmas. ψ_i, δ_m, and ϕ_c denote individual, month-year and classroom fixed effects. $MarketHourlyPay_{l,t}$ and $Weather_{l,t}$ denote the average market-level hourly pay and second-order polynomials of rainfall and snowfall, respectively, in the labor market l for individual i in week t. $\eta_{i,t}$ corresponds to the idiosyncratic shock. Finally, $I(t-t^*=y)$ denotes indicators for the week of the course, y, where t^* is the first week of the course ($y=0$). The excluded week is the week that is three weeks prior to the start of the course. Thus, each $\hat{\alpha}_t$ corresponds to the conditional mean of $CourseE_{i,t}$ for each week t (relative to the third week prior to the course start). Section 5 discusses the rationale for this specification. To appropriately capture the evolution of driving hours and study hours, we exclude individuals who drop modal course length) are presented in Figure 1. As expected, leading up to the beginning of the course, Canvas hours are essentially zero.[22] Hours spike to roughly 3 hours per week in the first week of class but decline monotonically throughout the course until the final week, where hours on Canvas spike again. Taken together, the results presented in Figure 1 suggest that students front-load study time as they adjust to the course (and perhaps the Canvas environment) and then taper down their Canvas activity each week until the final week of the term when they increase substantially, most likely reflecting students' preparation for final exams.

3.2 Uber Data

The Uber driver data include background characteristics and individual weekly driving activity corresponding to two groups of drivers: Uber-students and a random sample of drivers that qualify to participate in the ASU-Uber partnership program but did not enroll (henceforth, Uber peers). Additionally, we have access to city-level labor market characteristics and weather conditions.[23]

3.2.1 Characterizing ASU-Uber Drivers

Background Characteristics Table 4 shows how Uber-Students compare with Uber peers; Uber peers are drivers qualifying to participate in the program but not enrolling in ASU courses. Uber-students are, on average, more likely to be female and younger than their Uber peers. They are also less diverse in terms of language spoken (i.e., almost none speak Spanish) and more likely to work in Arizona than their driving counterparts (i.e., 6% vs. 2%). The bottom panel of this table also indicates that Uber students have longer Uber tenure than their peers. In particular, they have been driving for more than 128 weeks, and

out or withdraw at some point during the course.

[22]The point estimate for the week -1 is slightly above zero because some classes allow students to access the Canvas page the week before class begins (i.e., some students have non-zero Canvas hours in week -1). This is the reason why we set week -3 as the baseline.

[23]The drivers in our sample work in 111 distinct geographic regions/cities across the United States. Information on weather conditions was downloaded from the PRISM Climate Group at Oregon State University.

Table 4: Driver-level observables, by sample

	(1)		(2)		(3)
	Uber-Students		Uber Peers		Col (1) - (2)
	Mean	Std. Dev.	Mean	Std. Dev.	Difference
Background Characteristics					
Female	0.15	0.353	0.10	0.300	0.05***
Age†	43.74	10.68	50.63	12.83	-6.89***
English	0.99	0.072	0.91	0.292	0.09***
Spanish	0.00	0.051	0.07	0.254	-0.07***
Ever driven in AZ	0.06	0.237	0.02	0.149	0.04***
Uber activity					
Weeks in Uber data	128.91	27.568	111.75	37.757	17.16***
Active weeks in Uber data (%)	0.79	0.159	0.81	0.170	-0.02***
Lifetime completed trips	8118.40	4554.433	7798.29	4732.587	320.11***
Lifetime average rating	4.92	0.039	4.90	0.050	0.02***
Observations	1540		96513		

Note: "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Uber peers" corresponds to drivers that qualify to participate in the ASU-Uber partnership, but do not enroll in ASU courses. †Age is based on the decade of birth rather than the actual year of birth, as reported in Table 1 (this is how Uber released this information). English and Spanish refer to the primary language spoken by the driver, "active weeks" refer to weeks where driving hours were non-zero, and "lifetime" refers to the driver's entire driving history. "Lifetime average ratings" range from zero to five. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

during 78% of those weeks (i.e., 100 weeks), they have been active on the Uber platform. On average, they have completed more than 8,100 trips, indicating an important degree of attachment to driving with Uber. Overall, these drivers' activity level is large enough to suggest that Uber is likely their primary source of income. Finally, Uber-students have, on average, high Uber ratings consistent with the eligibility requirements of the ASU-Uber program.[24]

One important characteristic we do not observe is whether a driver (Uber-student or control) participates in other gig work (e.g., DoorDash, Instacart, Lyft). Though this may be relevant for some drivers, we believe this is less of a concern in our context because the drivers in our sample have a demonstrated strong attachment to Uber, given their relatively long driving histories.[25]

[24] Our final sample of Uber drivers that participate in the program is relatively small. We believe this is partly because our analysis is limited to a period when the program was less known.

[25] The existing evidence also suggests that most drivers do not use the Uber and Lyft platforms. Hyman et al. (2020), for example, find that less than one-third of drivers use both the Uber and Lyft platforms in Seattle.

Table 5: Weekly Uber-student driving activity

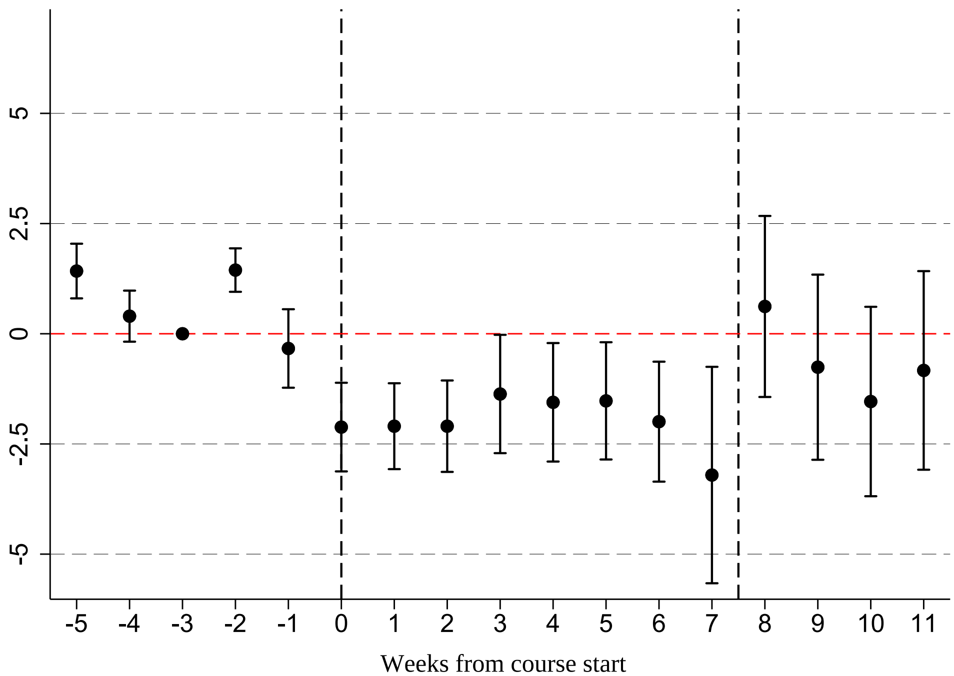
	Mean	Std. Dev.
Activity and trips		
Hours online	18.25	(17.29)
Completed trips	36.62	(35.74)
Uber earnings		
Weekly earnings	442.21	(461.71)
Earnings per trip	12.37	(5.67)
Earnings per hour	24.26	(9.89)
Tips per trip	1.12	(1.10)
Tips per hour	2.20	(2.25)
Average weekly rating	4.94	(0.13)
Observations	28896	

Note: Sample is limited to weeks in which drivers are enrolled in ASU classes. The variables "hours online", "completed trips", and "weekly earnings" include zeros for weeks that the drivers were inactive on the Uber platform. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Weekly Driving Engagement Table 5 shows weekly summary statistics on driving engagement when Uber-students are enrolled in classes at ASU. The top panel of Table 5 shows that, on average, Uber-students work (i.e., stay connected to the Uber platform) 18.25 hours per week and complete 36.62 trips. The bottom panel of the table indicates that Uber-students earn roughly $442 each week and that their earnings per trip (hour) is $12.37 ($24.26).[26] The final rows of Table 5 show that tips account for approximately 10% of Uber-students' earnings per trip or hour and that these drivers maintain exceptionally high ratings. To conclude, Appendix Table A5 shows the correlation between Uber activity (i.e., completed trips, time on the Uber platform) and total pay, incentive pay, and tips, indicating that hours online and completed trips are highly correlated, suggesting that idle time in the Uber platform is likely not a meaningful concern.

[26] Analogous summary statistics for Uber peers cannot be shown as it is considered sensitive information by Uber.

Figure 2: Event study results for driving hours during eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is hours on the Uber platform and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

3.2.2 Event Study of Weekly Uber Driving

As with study time, we augment the summary statistics in Table 5 by examining the evolution of driving hours throughout the course. To do this, we estimate an event-study specification, where the baseline week corresponds to the third week before a course begins.[27] Figure 2 displays the coefficients corresponding to the week of the course on driving hours in eight-week-long courses. We find that as drivers approach the beginning of a course, their driving hours seem to slightly taper off in week -1 and then drop by roughly two hours per week once the course starts. The decline in driving hours remains fairly constant across the semester, with an additional decline in hours (slightly over 2.5 hours per week) in the course's final week, which is when students prepare for exams. After the course ends, driving behavior

[27] The empirical specification follows eq. (6) described in Section 5, but replacing the covariate associated with coursework with indicators referring to the week of the semester (in a similar fashion as in eq. (1)).

is no longer statistically significantly different than pre-course levels. Interestingly, these results are consistent with our previous event study findings: we see that the increase in Canvas hours shown in Figure 1 is mirrored by a decrease in hours spent driving in Figure 2.

4 Analytical Framework

In this section, we lay out a simple model where agents have to balance effort between working and learning activities in a changing environment (i.e., incentives could change weekly). While the model is highly stylized, it will provide an economic justification for our empirical specifications presented in Section 5, and it will also allow us to quantitatively characterize how performing learning and working activities simultaneously impact the marginal cost of effort of each activity (in Section 7).

Agents' Maximization Problem Equation (2) poses the problem of the agent. Individual i has linear preferences at time t (e.g., week) over earnings and academic performance, where α denotes the weight assigned to each component. Earnings are determined by the wage rate at time t and work effort (i.e., driving hours or trips completed), $w_t e_{ilt}$, while academic performance is represented by coursework grade G_{it} (e.g., weekly college homework assignments, mid-term exams, etc.) at time t. In Equation (3), we define G_{it} as a function of individual-specific college effort (e_{ict}, study time), ability (Ab_i), and how difficult/demanding are college activities (ς_t), i.e., $G_{it} = f_i(e_{ict}, Ab_i, \varsigma_t)$. This linear specification of grades allows for (positive) complementarities in the production of grades between ability and college effort, and between course difficulty and college effort.

Exerting effort is costly and varies by type of activity, where λ_l and λ_c determine the cost associated with each type of effort. Finally, the model allows for (negative) complementarities in the cost of effort. For example, an additional working hour could be more costly (λ_{lc}) in weeks when the agent exerts more effort in college activities (e.g., driving an extra hour may be more daunting in weeks when college assignments have been more time-consuming). Finally, the additional constraints reflect basic/intuitive restrictions on α and $\lambda' s$. Given these preferences, the problem of the agent is to choose the optimal vectors of effort in each activity $(\mathbf{e}^*_{ic}, \mathbf{e}^*_{il})$.[28]

$$\max_{\mathbf{e}^*_{il}, \mathbf{e}^*_{ic}} \sum_{t=1}^{T} \Big(\alpha w_t e_{ilt} + (1-\alpha) G_{it} \Big) - \lambda_l \sum_{t=1}^{T} e^2_{ilt} - \lambda_c \sum_{t=1}^{T} e^2_{ict} - \underbrace{\lambda_{lc} \sum_{t=1}^{T} e_{ilt} e_{ict}}_{\substack{\text{Neg. complementarities of effort} \\ \text{btwn. work and college activities}}}, \tag{2}$$

where

$$G_{it} = \beta_0 + \beta_1 e_{ict} + \beta_2 Ab_i + \beta_3 e_{ict} Ab_i + \beta_4 \varsigma_t + \beta_5 e_{ict} \varsigma_t + \varepsilon_{it} \tag{3}$$

$$\alpha \in [0,1]$$

$$\lambda_l \geq 0, \lambda_c \geq 0, \lambda_{lc} \geq 0.$$

Optimal Effort The solution to the agent's problem is straightforward when we specify a linear production function for grades as in Eq. (3). The first-order-conditions of the agent's problem imply that the optimal levels of work and study effort satisfy:

$$e^*_{ilt} = \frac{(\alpha - 1)\lambda_{lc}[\beta_1 + \beta_3 Ab_i + \beta_5 \varsigma_t] + 2\alpha\lambda_c w_t}{4\lambda_c\lambda_l - \lambda^2_{lc}} \tag{4}$$

$$e^*_{ict} = \frac{2(1-\alpha)\lambda_l[\beta_1 + \beta_3 Ab_i + \beta_5 \varsigma_t] - \alpha\lambda_{lc} w_t}{4\lambda_c\lambda_l - \lambda^2_{lc}}. \tag{5}$$

Equations (4) and (5), while simple, are appealing and informative in several important ways. First, given that w_t and ς_t change at a high frequency in our context, incentives to

[28] As mentioned earlier, the goal of the model is to provide a framework to guide the empirical specification. Thus, the model is simplified along several dimensions. For example, the decision of each period is treated as static in nature. Similarly, Uber earnings are taken as given, and we do not allow for the possibility that individuals may strategically decide to drive at times within the week with higher rates. The last simplification is partly also made because we only observe Uber earnings at the weekly level.

exert effort on learning and working activities are likely to vary periodically. For example, as expected, the model predicts that a wage increase, $\uparrow w_t$, leads to an increase (decrease) in work (study) effort, while more demanding weeks of class, $\uparrow \varsigma_t$, lead to a likely decrease (increase) in work (study) effort.[29] The fact that, in most settings, it is not possible to directly observe effort in different activities makes our empirical context quite appealing to understand optimal effort decisions. Equations (4) and (5) also clarify that the solution to an agent's maximization problem only depends on exogenous variables that are independent of the agent's choices. This shows that it would be inconsistent with this type of economic model to empirically specify individual work effort as a function of individual college effort (regardless of the presence of instruments that could allow us to circumvent endogeneity issues).[30]

5 Empirical Strategy

Our baseline empirical approach has three fundamental goals. First, we intend to determine the impact of college coursework on labor market supply. This will allow us to quantify the short-run opportunity costs that students face when taking classes. To the best of our knowledge, this is the first paper that estimates this elasticity. Second, we aim to assess the effect of labor market conditions on course engagement. While many studies have determined how working hours affect academic performance, little is known about the role of transitory changes in labor market conditions on course activity and engagement. Finally, we study the impact of study effort on academic performance.

[29] It is expected that β_3 and β_5 are positive due to likely positive complementarities between effort and ability/college activities' difficulty.

[30] Wooldridge (2015) provides a discussion on this point. In particular, Wooldridge (2015) argues that an improper use of simultaneous equations models would be to model weekly hours spent studying and weekly hours working. Each student chooses these variables simultaneously as a function of the wage that can be earned working, ability as a student, etc. Therefore, it is incorrect to specify two equations where each is a function of the other.

5.1 The Impact of Learning Activities on Labor Market Supply

We rely on weekly individual-level data on driving and college engagement to uncover the effect of overall college coursework on labor supply. Our baseline specification, which is motivated from Equation (4), is as follows:

$$\begin{aligned} WorkE_{i,t} = \beta_0 + \beta_1 \sum_c CourseWork_{c,t} + \beta_2 MarketHourlyPay_{l(i),t} \\ + \beta_3 Weather_{l(i),t} + \psi_i + \delta_m + \phi_b + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where $WorkE_{i,t}$ denotes work effort/labor supply for individual i in week t. In our setting, we measure work effort as either hours connected to the Uber platform or completed trips. $CourseWork_{c,t}$ corresponds to the intensity of weekly activities in course c, which is captured by the weekly average hours that course peers stay connected to Canvas or by the average number of weekly assignments submitted by peers in the course. Note that we sum $CourseWork_{c,t}$ across all the courses c in which the Uber-student is enrolled in week t. $MarketHourlyPay_{l(i),t}$ denotes average active hourly pay for all drivers in week t and city l who are eligible for the ASU program but do not enroll, capturing labor market conditions at the location level.[31] $Weather_{l(i),t}$ controls for precipitation and temperature in order to account for shocks that could simultaneously affect labor supply and Uber earnings. ψ_i is an individual fixed-effect that captures driver and city-level unobserved heterogeneity.[32] δ_m is a month-year fixed effect that accounts for seasonality in the labor market, and ϕ_b corresponds to fixed effects representing the bundle of courses in which the student is enrolled in each

[31] Market level average active hourly pay is determined by dividing average total earnings by the average number of active driving hours for the peer drivers in a given city-week. In addition to active hours, we also observe average inactive hours (i.e., including idle time) on the Uber platform at the city-week level which allows us to construct a measure of market-level hourly pay that accounts for idle time. Our results are robust to using either definition of market-level pay, but we prefer active hourly pay because we think this is the more salient measure of compensation for drivers. There is substantial variation in market-level weekly hourly pay, where the standard deviation of this variable is \$5.5 in the sample. In addition, there is both substantial variation across cities, as well as within cities across weeks. The standard deviation in weekly hourly pay across cities is \$4.3, and within cities across weeks is \$3.5.

[32] Individual fixed effects also serve to account for students' study time outside the ASU platform, operating under the assumption that the ratio of study time apportioned within and outside the ASU online platforms remains stable across weeks.

term.[33] Finally, $\epsilon_{i,t}$ represents an idiosyncratic shock.

The main coefficient of interest is β_1 which indicates how college activities impact labor market productivity/supply, characterizing short-run opportunity costs of attending college. Our key identifying assumption is that once conditioning on individual, course-bundle, and month-year fixed effects, the variation in weekly Canvas activity of ASU-Online peers represents exogenous changes in college activities/tasks. Given the time spans used in the analysis, we believe the assumption of time-invariant individual characteristics is quite reasonable. Finally, the fact that we exploit individual-level variation within college terms, usual concerns in this literature regarding the role of pre-college enrollment disengagement effects is not likely to be relevant in our setting. We also estimate more robust specifications that include city-week fixed effects. However, such an empirical model prevents the identification of β_2.

Our estimate of β_2, while not the object of study, reflects the responsiveness of labor supply to changes in average hourly earnings across weeks at the market level. The identification of this parameter requires stronger assumptions. In particular, it is necessary to impose orthogonality between unobserved factors impacting weekly city-level earnings and worker i's labor supply. The main instance in which this condition may not hold is when weather conditions (e.g., precipitation) affect both hourly pay (through demand) and the desire of drivers to spend time on the road (driving on rainy days may be more inconvenient). As a result, we have included controls for weekly average precipitation and temperature to avoid this concern.[34] However, it is still possible that other factors may be operating in a similar fashion. In summary, β_2 should be interpreted with caution.

[33] In the data, a large proportion of students share the same bundle of courses. Moreover, we also exploit differences in the bundle of courses across semesters within individuals.

[34] Though not a threat to identification per se, including student-drivers who have dropped out of their courses in our sample could complicate our interpretations of $\hat{\beta}_1$ and $\hat{\beta}_2$. As a robustness check, we also estimate our main regression specifications on a subset of the sample that excludes likely dropouts. We determine likely dropouts based on their final course grades (e.g., incomplete or withdrawals) and their activity. Specifically, if a student receives a failing grade, an incomplete, or a withdrawal *and* has a spell of inactivity for at least the final three weeks of the course, we consider them a likely dropout. Directly excluding these individuals has little effect on our coefficient estimates. See Appendix A for more details on this point.

5.2 The Impact of Labor Market Conditions on College Effort

As with our main estimating equation for the effect of earnings and coursework on hours driving, we derive our baseline specification to identify the impact of labor market conditions and coursework on student effort from Equation (5) of the analytical model. The primary estimating equation is:

$$\begin{aligned} CourseE_{i,c,t} = \delta_0 + \delta_1 CourseWork_{i,t,c} + \delta_2 \sum_{-c} CourseWork_{i,t,-c} \\ +\delta_3 MarketHourlyPay_{l(i),t} + \delta_4 Weather_{l(i),t} + \delta_5 X_{c,t} + \pi_i + \alpha_m + \rho_c + \eta_{i,c,t}, \end{aligned} \tag{7}$$

where $CourseE_{i,c,t}$ denotes course level effort of student i on class c during week t.[35] Course effort is captured by the number of weekly hours the student spends on Canvas, the weekly number of clicks, or logins in course c. $CourseWork_{i,t,c}$ measures course activities in course c captured by the number of Canvas hours, clicks, or logins of the peers in the class, while $CourseWork_{i,t,-c}$ also captures course peer activities but in the other courses ($-c$) in which the student is enrolled in. $X_{c,t}$ denotes number of course days in the week and π_i, α_m, and ρ_c denote individual, month-year and classroom fixed effects.[36] Finally, $MarketHourlyPay_{l(i),t}$ and $Weather_{l(i),t}$ have the same definition as in Equation (6). Note that this specification controls for classroom fixed effects rather than for bundle of courses, where a classroom is defined as a given course with a given instructor in a given term. $\eta_{i,t}$ corresponds to the idiosyncratic shock.

The parameter of interest from this empirical model is δ_3, which indicates how sensitive college effort is to labor market conditions. The implicit assumption is that conditional on the vector of fixed effects, observables, and weather conditions, we identify the reduced-form effect of Uber rates on course effort. As a robustness check, we implement a placebo test (in

[35] While the previous specification relies on observations at the individual-week-level, this specification involves observations at the individual-course-week-level.

[36] We include the number of course days in the week as a control because some weeks of class (such as the first and final weeks of the course) do not start on Monday or end on Friday. As a result, Canvas activity is, in a sense, mechanically lower due to fewer days of potential activity.

Table 7) to test for the validity of this assumption.

5.3 The Effect of Labor Market Effort on Academic Performance

Finally, we study how work effort and labor market conditions impact academic performance. To this end, we propose two specifications. First, we analyze the direct effect of Uber driving hours on course grades by estimating the following equation:

$$CourseG_{i,c} = \gamma_0 + \gamma_1 f(\textstyle\sum_t WorkE_{i,t}) + \psi_i + \phi_c + \eta_{i,c}, \tag{8}$$

where $CourseG_{i,c}$ denotes student i's final grade in course c. ψ_i and ϕ_c denote individual and classroom fixed effects, respectively. $WorkE_{i,t}$ denotes Uber work hours in week t, where the sum is over the total number of weeks in the academic term, and f corresponds to a flexible function.[37]

Second, we assess the impact of labor market conditions on academic performance by estimating a similar specification as in eq.(8), but replacing work effort with college effort.[38] By doing so, we can combine the estimates on college effort from this specification with those obtained from eq.(7) to provide a back-of-the-envelope calculation of the effect of labor market hourly pay on academic performance through its impact on course effort.

6 Results

6.1 Course Work and Labor Market Supply

Table 6 shows the estimates corresponding to Equation (6), i.e., how college activity impacts hours driven and completed trips. Columns (1) and (4) indicate that a 10% increase in av-

[37] Due to the inclusion of individual fixed effects, variation in performance across academic terms (i.e., 7 to 8 weeks) identify the effects of work effort on course grades.

[38] College effort is a mediating variable for the effect of work effort on academic performance. Therefore, the effect of work effort on academic performance once conditioning on study effort is expected to be close to zero.

erage learning activities decreases average driving time or completed trips by approximately 1% (reported at the bottom of the table). Considering that, on average, peers are engaged 2.45 hours per week on the Canvas platform, our estimates imply that the average Uber-student decreases driving time by approximately 1.7 hours (-0.680 $\times$ 2.45) each week due to coursework.[39] Coupled with the fact that Uber-students earn roughly $24 per hour, we interpret these findings as suggesting that the average short-run opportunity cost of college enrollment is approximately $41 per week or $180 per month. Columns (2)-(3) and (5)-(6) show that our estimates are robust to controlling for weather conditions or city-week fixed effects.[40,41] Appendix Table A7 shows that further controlling for leads and lags of the independent variables (i.e., the prior and following weeks) does not meaningfully change the effect of study hours on work effort. This is somewhat expected, given that our baseline specifications already control for individual fixed effects.

As discussed in Section 3.1, our measures of study effort are potentially incomplete, which may bias our estimates of the effect of course demand on driving hours. However, we are reassured by the fact that our results are qualitatively and quantitatively consistent across Table 6 and Figure 2.[42] Specifically, we see that in both cases, the overall response of Uber hours to coursework is relatively small.

Finally, the estimates corresponding to labor market conditions presented in Table 6 (which should be interpreted with caution per the discussion in Section 5.1) show that a $1 increase on average hourly pay increases average weekly Uber hours by 0.122 hours (i.e., 7.3 minutes) or 0.35 trips per week.[43] If we consider that the average *active* hourly pay of drivers

[39]Projecting peers' Canvas hours onto Uber-students' actual Canvas hours yields a coefficient close to 1.

[40]The number of observations vary slightly across columns because weather data are not available for some cities. In addition, for some city-weeks, there is only one observation; specifications with city-week FEs drop such cases.

[41]Given the city-week fixed-effects included in our specifications for Columns (3) and (6), we are somewhat limiting the level of identifying variation available. Reassuringly, though, we see that there are, on average, 26 observations in each city-week (ranging from 2 to 73 observations per city-week). Additionally, Appendix Table A6 shows results corresponding to specifications that include the number of course assignments as a measure of course effort. Findings show similar patterns to those described in Table 6.

[42]Note that the event study estimates do not rely directly on measures of study effort, since course activities/demand are replaced by indicators for week of the semester.

[43]The top subfigures of Appendix Figure A2 present the distribution of the labor supply elasticity w.r.t

Table 6: Determinants of work effort

	(1) Work Hours	(2) Work Hours	(3) Work Hours	(4) Completed Trips	(5) Completed Trips	(6) Completed Trips
Sum of avg. study hours across all c, peers	-0.680***	-0.678***	-0.667***	-1.283***	-1.279***	-1.311***
	(0.071)	(0.072)	(0.100)	(0.146)	(0.146)	(0.205)
Market level active hourly pay, currently elig.	0.122**	0.132**		0.351**	0.381**	
	(0.051)	(0.051)		(0.112)	(0.113)	
Obs.	27475	27404	26265	27475	27404	26265
Individual Fixed Effects	✓	✓	✓	✓	✓	✓
Course Bundle Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed effects	✓	✓		✓	✓	
Weather controls		✓			✓	
City-Week FE			✓			✓
Mean dep. var.	18.24	18.21	18.39	36.52	36.48	36.78
Market level active hourly pay, peers	33.62	33.61		33.6	33.6	
Sum avg. study hours all c, peers	2.45	2.45	2.46	2.45	2.45	2.46
Mean hourly earnings	24.23	24.22	24.38	24.23	24.22	24.38
Mean pay-per-trip	12.37	12.37	12.46	12.37	12.37	12.46
Elasticity w.r.t. peer coursework	-0.091	-0.062	-0.089	-0.086	-0.086	-0.088
Elasticity w.r.t. peer earnings	0.225	0.244		0.323	0.351	

Note: The dependent variables for Columns (1) to (3) and Columns (4) to (6) are weekly work hours and weekly completed trips, respectively. The variable "Sum of avg. study hours across all c, peers" denotes the sum of the average hours per week that peers spent on Canvas across all courses. The variable "Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Specifications include multiple sets of fixed effects. Course bundle fixed effects denote the set of courses taken in a given term. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Elasticities are calculated by multiplying the relevant coefficient estimates by the ratio of mean peer coursework or market-level hourly earnings to the mean of the dependent variable. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

that do not attend ASU is \$33.60, and that the average weekly driving time among Uber-students is 18.24 hours, then a 10% increase in average hourly pay leads to an increase in driving time (trips) of roughly 2.3% (3.2%). Caldwell and Oehlsen (2022) finds that the Frisch elasticity for Uber male drivers (our sample is overwhelmingly male) is somewhat higher than the elasticity we estimate (4%). However, two reasons could explain the differences in findings. First, Caldwell and Oehlsen (2022) estimates labor supply elasticities using random variation generated by an experiment that allowed drivers to work for one week with 10-50% higher earnings per trip. Given that the experiment explicitly highlighted the possible gains from additional driving hours, we expect drivers to be more responsive in their labor supply in this context. Second, our sample of drivers tends to have a stronger attachment to work (i.e., they consistently drive more hours per week than the average Uber driver), likely making them less responsive to changes in market hourly pay.[44]

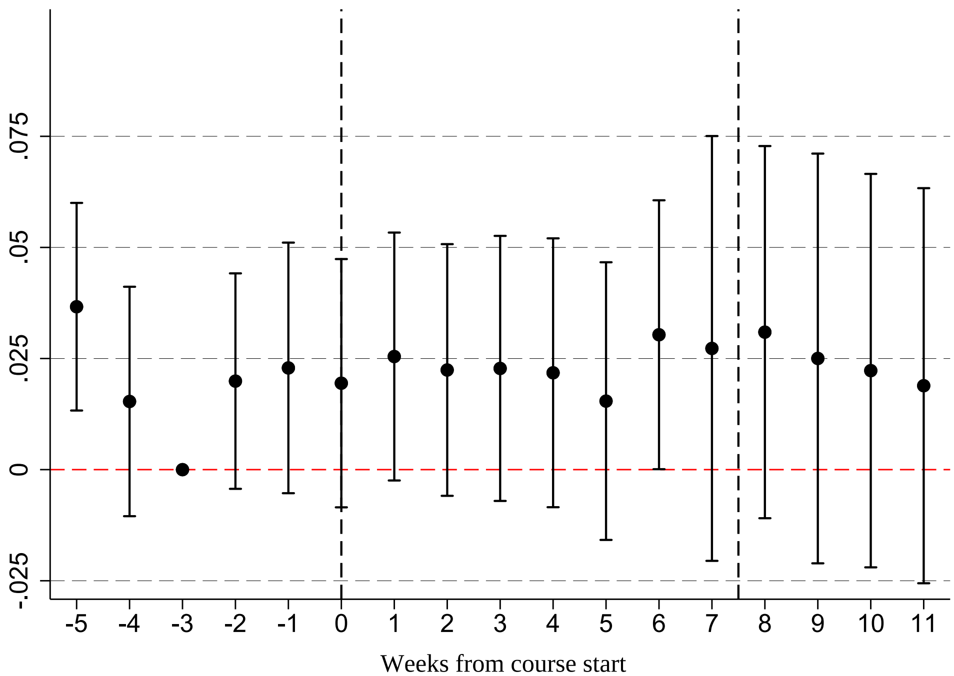
We can also analyze whether the quality of the service that drivers offer is affected by college activities. To this end, we performed similar event studies as in Section 3.1 but included as dependent variables the ratings the drivers received from their passengers and the share of income from tips. Figure 3 shows no negative impact on ratings, while appendix Figure A1 shows a small drop in the fraction of earnings coming from tips, but the economic impact is extremely small (a decrease of 1 percentage point in the share). Thus, we conclude that college activities have no meaningful impact on the quality of service.

Overall, our findings indicate that the "short run" opportunity cost of attending college in this context (i.e., \$180 per month) is small relative to the average earnings that Uber-students make when taking classes at ASU (i.e., approx. \$2,200 per month). We also do not observe any meaningful negative impacts on the quality of work performed.

course work and earnings (i.e., calculated based on the average course work and market-level hourly earnings of each Uber-student).

[44] This difference in labor supply elasticity does not appear to be specific to Uber drivers in the Uber-ASU program. We estimate an elasticity of 2.7% for a sample of non-ASU Uber drivers who were eligible for the program but never enrolled.

Figure 3: Event study results for driver ratings during eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is average driver rating and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

6.2 Labor Market Conditions and Study Effort

Table 7 presents results from estimating the effects of labor market conditions and college course demand on Uber-students Canvas hours. Evidence on how variation in weekly earnings impacts study effort is scarce. Thus, the estimates in Table 7 are unique in that they quantify the extent to which Uber-students are willing to sacrifice study time for higher income in the short run. Column (1) shows that a $1 increase in average hourly pay decreases study hours by less than a minute, or in other terms, a 10% increase in average hourly pay leads to a decrease in study time for the mean Uber-student of approximately 1.7% per course; note that we express the results in minutes rather than hours (which is the unit of the dependent variable) to ease interpretation. This result suggests that study time is not highly sensitive to changes in labor market conditions, at least in this context.[45] However, this finding could be specific to our context, given that flexibility may allow drivers to spend more time on the Uber platform when earnings are high without meaningfully decreasing their study time. We also find that average peer Canvas hours have a nearly one-to-one relationship with Uber-student study hours, suggesting that our measure of course demand effectively captures the variation in college work across weeks.[46] Surprisingly, we do not find much evidence of crowding out between courses, given that an increase in coursework demand in other courses, $-c$, does not impact study time in course c. Column (2) performs a similar analysis as in column (1), but instead of including peer hours on Canvas, we measure coursework demand by the number of assignments in a given week in course c. Results show that having an additional assignment increases weekly average study hours in course c (i.e., 1.58 hours) by around 3% (i.e., 0.046/1.58).

Finally, Column (3) presents results from a placebo test to check the extent to which market-level hourly pay may be capturing some unobserved shock that is not captured by our controls. For example, suppose weather conditions (which we control for) simultaneously affect study hours and earnings. In that case, we should observe a mechanical correlation between weekly earnings and study hours for students who do not drive with Uber. To this end, we repeat the specification in Column (1) but on the sample of students attending ASU-Online classes but not participating in the Uber-ASU program. Reassuringly, we find a coefficient of zero for these students. To conclude, Appendix Table A8 presents results where we further control for leads and lags of the independent variables to understand how

[45] To provide a comparison–albeit an imperfect one–to our findings, the study by Lee (2020) shows that a 10% increase in the minimum wage leads to a 5.2% decline in part-time enrollment at community colleges. However, this increase in minimum wage seemingly has a negligible and statistically insignificant impact on full-time enrollments. Contrarily, research by Alessandrini and Milla (2021) indicates that a 10% rise in the minimum wage leads to a 1% decline in post-secondary enrollments. However, this overall effect obscures substantial underlying heterogeneity. Specifically, a 10% enhancement in minimum wage is associated with a 5% reduction in university enrollments while simultaneously inducing a 6% increase in enrollments at community colleges.

[46] The bottom subfigures of Appendix Figure A2 present the distribution of course effort elasticity w.r.t course work and earnings (i.e., calculated based on the average course work and earnings of each Uber-student).

Table 7: Determinants of study effort

	Study Hours in c (1)	Study Hours in c (2)	Placebo Test (3)
Avg. study hours in c, peers	1.134***	-	1.022***
	(0.027)		(0.018)
Sum of avg. study hours in $-c$, peers	-0.009	-	-0.007***
	(0.006)		(0.002)
Assignments graded in c	-	0.046***	-
		(0.015)	
Sum of assignments graded in $-c$	-	-0.012**	-
		(0.005)	
Market level active hourly pay, currently elig.	-0.008**	-0.029***	-0.001
	(0.004)	(0.004)	(0.001)
Observations	55293	55293	555752
Individual Fixed Effects	✓	✓	✓
Classroom Fixed Effects	✓	✓	✓
Month-Year Fixed effects	✓	✓	✓
Weather controls	✓	✓	✓
Mean dep. var.	1.58	1.58	-
Avg. study hours in c, peers	1.27	-	-
Sum avg. study hours in $-c$, peers	1.55	-	-
Assignments graded in c	-	2.21	-
Sum assignments graded in $-c$	-	2.78	-
Market level active hourly pay, peers	33.6	33.6	-
Elasticity w.r.t. peer coursework	0.912	0.064	
Elasticity w.r.t. peer earnings	-0.170	-0.617	

Note: The dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. "Assignments graded in c" and "Sum of assignments graded in $-c$" denote the number of assignments graded in course, c, and all other courses, $-c$ for a student in a given week. The results in Column (2) are from a 2SLS specification where "Assignments graded in c" and " Sum of assignments graded in $-c$" are instrumented with the average graded assignments for non-Uber peers in c and $-c$, respectively."Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Specifications include multiple sets of fixed effects. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. Elasticities are calculated by multiplying the relevant coefficient estimate by the ratio of mean peer course work or market level hourly earnings to the mean of the dependent variable. Standard errors are clustered at the class level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

this would impact the effects reported in Table 7 (i.e., current effects at time t). We find that the coefficients remain quite robust across specifications.[47]

[47] Appendix Table A9 replicates the analysis in Table 7 but weekly clicks and logins replace study hours as the dependent variables. The results across all of these models are qualitatively very similar.

Table 8: Heterogeneity in the determinants of study and work hours

	Full-time driver (1)	STEM (2)	Female (3)	High-need (4)	High Incoming GPA (5)
Panel A: Work hours					
Sum avg. study hours all c, peers	-0.381***	-0.360***	-0.497***	-0.554***	-0.465***
	(0.090)	(0.092)	(0.094)	(0.132)	(0.115)
Sum avg. study hours all c, peers × var. in top row	-0.237*	-0.285**	0.166	0.079	0.027
	(0.137)	(0.136)	(0.157)	(0.144)	(0.134)
Observations	27404	26636	26690	27388	23902
Panel B: Study hours					
Market level active hourly pay, currently elig.	-0.010**	-0.007	-0.007*	-0.011*	-0.007
	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)
Market level active hourly pay, currently elig. × var. in top row	0.006	-0.001	-0.015	0.003	-0.003
	(0.006)	(0.006)	(0.010)	(0.007)	(0.006)
Observations	55293	53731	53975	55266	48263

Note: This table only reports the relevant coefficients, though the specifications follow equations (6) and (7) but with the inclusion of the relevant interactions with the different subgroups. Appendix Table A10 shows all the specification coefficients. For Panel A—the dependent variable in each column is hours working on the Uber platform. "Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership but not enrolled. "Sum of avg. study hours across all c, peers" denotes the sum of the average hours per week that peers spent on Canvas across all courses. For Panel B—the dependent variable in each column is weekly study hours in course *c*. "Avg. study hours in *c*, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course *c*. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides *c*. All specifications include multiple sets of fixed effects, second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. In Panel A, standard errors are clustered at the individual level. In Panel B, standard errors are clustered at the class level.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

6.3 Heterogeneous Effects

Next, we examine whether changes in coursework loads and labor market conditions lead to differential responses based on Uber-students' observable characteristics. In particular, we consider: i) full-time or part-time driver status, since time constraints may be more binding for full-time drivers; ii) field of study, since certain majors may be more demanding than others; iii) gender, as prior literature demonstrates that labor supply choices may differ by the gender of the driver (Cook et al., 2021; Caldwell and Oehlsen, 2022); iv) financial need status, since labor supply may be more inelastic to changes in coursework demand for this group, and; v) incoming academic performance (above- vs. below-median incoming GPA), as certain students may be more responsive to coursework demands.

Panels A and B of Table 8 present results from re-estimating equations (6) and (7), respectively, but interacting the independent variables of interest with the different student observables. Column (1) of Panel A shows differential responses between full-time and part-time drivers; we define full-time drivers as those who, on average, drive at least 25 hours per week when not enrolled in courses. We find that the labor supply of full-time drivers is more responsive to coursework activities, which is consistent with the fact that part-time drivers have more flexibility to avoid altering their labor supply in response to higher coursework responsibilities. Column (2) of Panel A also shows that STEM majors are more prone to reduce their working hours (compared to non-STEM majors) in response to coursework demands. In particular, STEM students' labor supply is roughly 45% more responsive to changes in college activities than non-STEM ones. This finding was expected given that STEM majors often take more demanding courses (in terms of peer hours).[48] Finally, we do not find statistically significant differences in the responsiveness of work hours based on gender (Column 3), financial need status (Column 4) or incoming GPA (Column 5).[49]

Panel B of Table 8 explores heterogeneous effects on Canvas (study) hours. For the most part, we find little systematic heterogeneity in terms of how labor market conditions impact study hours. As in Panel A, we see the female students' study hours are more responsive to market-level hourly pay, but the estimate is not statistically significant at conventional levels.

7 Decomposing the Cost of Effort

In this section, we attempt to decompose the marginal cost (MC) of study and work effort by quantifying what proportion of these costs can be attributed to (negative) complementarities arising from performing both activities simultaneously. For example, we aim to determine

[48] Our estimates indicate that the return to an individual hour of time spent on Canvas is lower in terms of course grades for STEM students. Specifically, we find that the return to an hour of time on Canvas is only 70% as high compared to non-STEM students. This suggests that STEM majors need to spend relatively more time on Canvas in response to their course activities. In fact, we find that, on average, Uber and non-Uber students in STEM majors spend over two hours more on Canvas for each course.

[49] In economic terms, female students' labor supply is two-thirds as responsive as males' to coursework demands, but the estimate is not precise. The lack of statistical significance in heterogeneity by gender could be due to the small sample sizes.

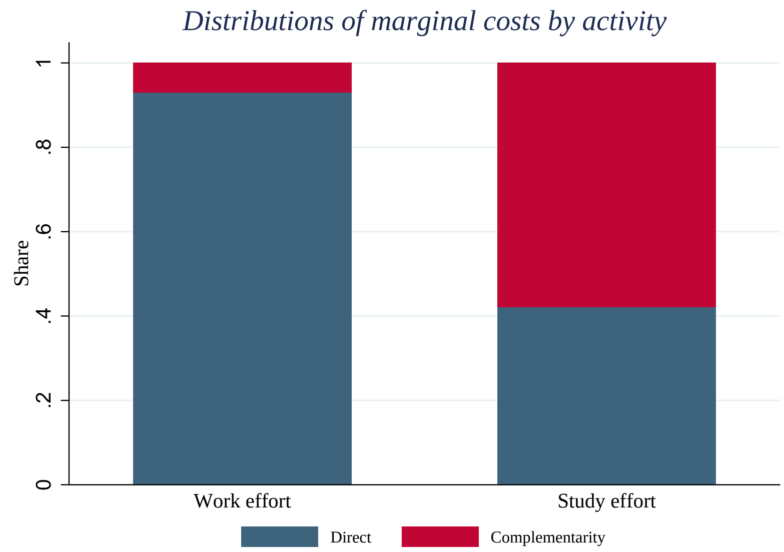


Figure 4: Contributions of direct effects and complementarities to marginal costs

what share of the total weekly marginal cost of driving can be explained by school effort exerted in a given week.[50] To this end, we take advantage of the fact that it is possible to estimate reduced-form specifications closely linked to our analytical model's first-order conditions (presented in Section 4) and therefore compute the following ratios: $\frac{\lambda_{lc}}{\lambda_l}$, $\frac{\lambda_{lc}}{\lambda_c}$.[51] Then, we can use them jointly with the expressions for the marginal costs derived from our analytical framework to separately identify the share of the MC coming from direct efforts when exerting each activity and from performing both activities simultaneously. Appendix B provides a detailed description of how we implement this decomposition. Figure 4 presents the proportion of the marginal costs arising from complementarity effects (i.e., performing both activities simultaneously) and direct effects, where we condition on the average weekly hours of the working and learning population. The results indicate that, at the average level of work and study hours, roughly 9% of the total marginal cost of working is attributable to additional costs introduced when engaging in both activities simultaneously. Interestingly, this share is much larger for learning activities, where roughly 56% of the total marginal

[50]For example, the cost of an additional hour of driving could be more daunting if an individual has been studying many hours during the week.

[51]See eq.(2) for definition of the λ's.

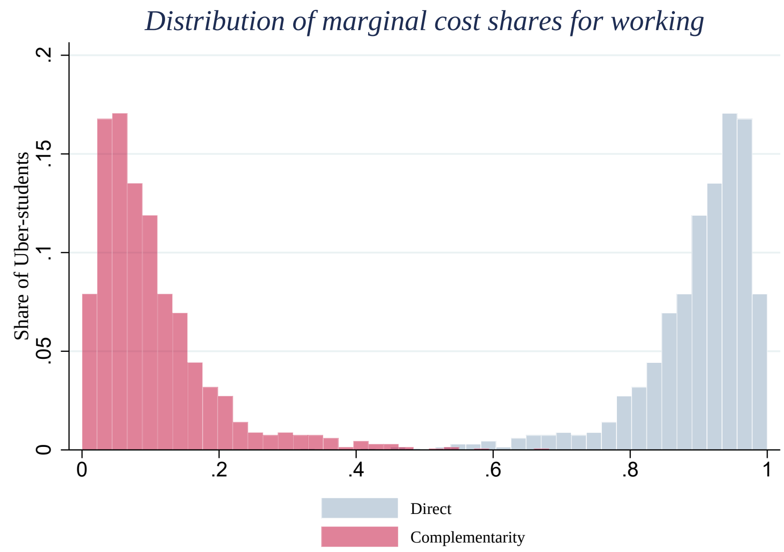


Figure 5: Distribution of the direct effect share of marginal cost of working

cost is due to these negative complementarities. However, this result is mainly driven by the fact that, in our sample, Uber-students spend more time performing working rather than learning activities. Finally, we find that $\dfrac{\lambda_l}{\lambda_c} = 0.35$, suggesting that the disutility cost of studying is approximately three times larger than the one from working.

In addition to analyzing the relative shares for average work and study hours, we also uncover their distribution based on each individual's average driving and studying behavior.[52] Figure 5 plots the distribution of the share of marginal costs of working that is attributable to the direct costs of working (in blue) and due to the negative complementarities between working and studying (in red), while Figure 6 is analogous but for studying. These figures show that there is substantial heterogeneity in the exact source of marginal costs for these two activities (driven by the combination of hours chosen), particularly for learning activities. For example, there is very little extra cost associated with studying while working (separate from the direct costs of each activity) for some Uber-students; whereas for others, the combination of these activities together appears to be substantially more costly.

[52] A key assumption behind this exercise is that the structural parameters of our model are constant across the population but that individuals still have variation in their optimal driving behavior based on differences in earnings and course requirements. These differences yield variation in the relative contribution of direct effects and complementarities to the marginal cost of each activity.

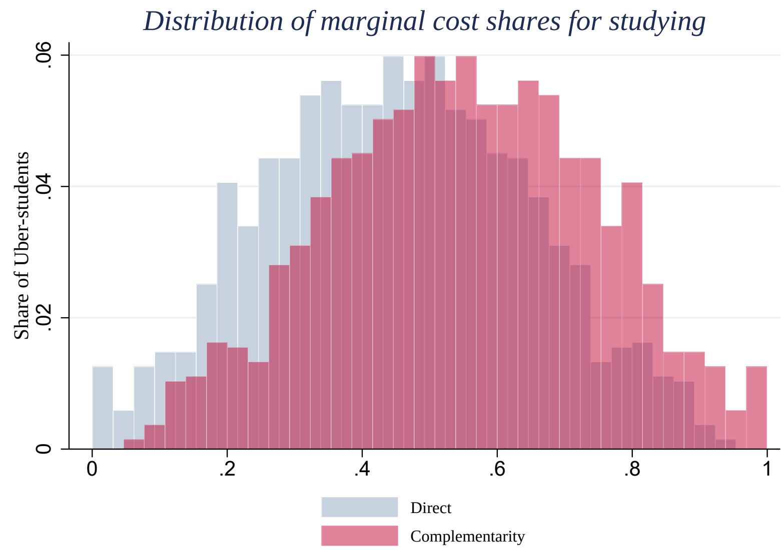


Figure 6: Distribution of the direct effect share of marginal cost of studying

8 The Role of Flexibility

The large degree of flexibility in this working-learning context is a priori unique. Therefore, it is important to assess whether Uber-students exploit such flexibility when, for example, facing higher demand in course activities. Moreover, the results presented in Section 6 thus far suggest that most Uber-students face a relatively small trade-off when allocating time between school and work. One potential explanation for this is the unique flexibility of our empirical setting, especially relative to more standard work or school arrangements.

To this end, we construct a dissimilarity index that captures deviations in the driving schedules of Uber-students from their typical driving patterns when not enrolled in classes. In particular, our data allows us to observe how drivers distribute their time on the Uber platform across 28 six-hour periods in each week; for example, the first period is Monday morning from 12:00 AM to 6:00 AM and the second is Monday from 6:00 AM to 12:00 PM. We use these data to construct an index that reflects overall deviations from a driver's usual driving schedule when not enrolled at ASU. In a given week, t, Uber-student i's total dissimilarity index is equal to:

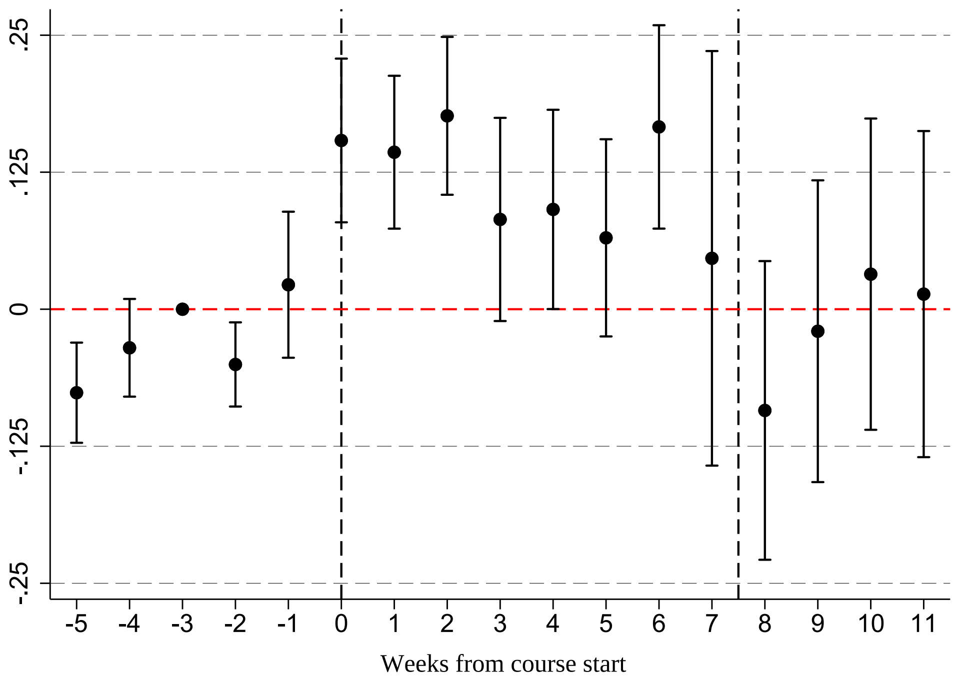
$$D_{i,t} = \frac{1}{2}\sum_{p=1}^{28}\left|\frac{\bar{m_{i,p}}}{\bar{M_i}} - \frac{m_{i,p,t}}{M_{i,t}}\right|,$$

where p refers to one of the 28 six-hour periods, $m_{i,p,t}$ is the total minutes driven in period p in week t, $M_{i,t}$ is the total number of minutes driven in week t, $\bar{m_{i,p}}$ is the average minutes driven across all p periods in non-ASU weeks (i.e., when not enrolled in classes), and $\bar{M_i}$ is the average number of minutes driven across non-ASU weeks. This index aims to capture changes in the distribution of hours worked across periods within the week, while accounting for the fact that total hours worked may differ substantially between ASU and non-ASU weeks. For example, $D_{i,t} = 0$ implies no change in behavior, while the maximum value in our sample of 1 suggests a fully dissimilar schedule (i.e., the distribution of hours driven in the week does not overlap with their average non-ASU schedule). In practice, for the analysis and to ease interpretation, we have standardized the dissimilarity index values.

8.1 Flexibility Results

Figure 7 presents results from an event-study specification similar to those previously presented but using the (standardized) dissimilarity index described above as the dependent variable. Each of the coefficient estimates presented in Figure 7 should be interpreted as a percent of a standard deviation (with Week -3 corresponding to the baseline week). The more negative the standardized dissimilarity index, the less the Uber-students change their behavior driving during the class period when compared to non-enrollment periods. For example, the coefficient on the first week of courses (week zero) shows that the overall dissimilarity index increases by roughly 14% of a standard deviation for the average Uber-student. We interpret these results as indicating that within-week flexibility increases when college activities become more demanding at the beginning and end of the academic term (see Figure 1) and, as study time declines in the middle of the course, so does the value of

Figure 7: Event study results for within week driving flexibility for eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is the standardized dissimilarity index and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

within-week flexibility. The patterns in Figure 7 indicate that students do, in fact, adapt to their new schedules (i.e., finding time for their schoolwork that does not sacrifice optimal driving hours) as the courses progress.[53]

Overall, the results in this section suggest that within-week flexibility plays a measurable role for this sample of Uber-students. That said, we suspect that our findings represent a lower bound on the role (and value) of this type of flexibility. First, we can only observe within-week flexibility in our Uber data. It is likely that the asynchronous nature of the Canvas courses also allows Uber-students to better optimize their work and study time in a

[53]These event-study coefficient estimates translate to an average treatment effect across weeks that can be summarized as follows: when the average study time of their peers increases by one hour per week, on average, drivers deviate from their typical schedule by roughly 4.1% of a standard deviation. Moreover, Appendix Figure A3 presents similar results where we construct the dissimilarity index specifically for typical peak hours periods (i.e., Friday and Saturday afternoons and nights). The results from the figure suggest that these driving behaviors during those hours are particularly likely to adjust during courses.

way that is not captured in our analysis. This may be especially relevant to our findings that study hours have a relatively small effect on driving hours. Second, our measure of flexibility in the Uber data is still fairly rough. In particular, our data do not allow us to identify any flexibility taking place within the six-hour windows we observe. Finally, we cannot see how earnings are distributed throughout the week. Therefore, we cannot observe if drivers are responding to within-week price variation to maximize the productivity of their driving time.

9 Effort Measures and Academic Performance

To conclude, we study how working hours and labor market conditions affect student performance (i.e., course grade points). Table 9 shows results corresponding to three specifications that all control for individual and classroom fixed effects, as described in Section 5.3. Columns (1) and (2) consider total Uber (work) hours, while columns (3) and (4) refer to specifications that flexibly account for Canvas (study) hours. The specifications in columns (2) and (4) instrument Uber-students' total hours on Uber and Canvas with the average (across weeks) market level pay for eligible drivers and average total hours on Canvas of the class peers, respectively, as a robustness check.[54] Three main takeaways emerge from these specifications. First, driving hours do not seem to impact course grades. Second, based on the estimates from the IV specification, we find that a 10% increase in the average total Canvas hours (i.e., 1.37 hours) increases course grades by 0.28 points (i.e., $1.37 \times 0.202 - (1.37)^2 \times 0.001$), approximately one-fourth of a letter grade.[55] This result indicates that Canvas hours are strongly associated with course performance, suggesting that, though imperfect, our measure of study hours is highly relevant. Finally, using these estimates, it is possible to provide a back-of-the-envelope calculation to quantify how changes

[54]Note that class peers do not include other drivers that use the Uber app. Also, we hesitate to interpret the estimates in column (2) as causal given our relatively weak first-stage.

[55]We present similar results for other measures of course-level outcomes (i.e., course completion and having a passing grade) in the Appendix (see tables A12 and A13). In addition, specifications simultaneously controlling for Uber and Canvas hours provide almost identical results.

Table 9: The effect of work and study effort on course grade points

	(1) Course Grade Points	(2) Course Grade Points (IV)	(3) Course Grade Points	(4) Course Grade Points (IV)
Total Uber hours	0.001	0.013	-	-
	(0.001)	(0.054)		
Total Uber hours^2	-0.000	-0.000		
	(0.000)	(0.000)		
Total Canvas hours	-	-	0.107***	0.202***
			(0.006)	(0.027)
(Total Canvas hours)^2	-	-	-0.001***	-0.001***
			(0.000)	(0.000)
Obs.	4900	4900	4900	4900
Adjusted R^2	0.55	.	.64	.
Individual Fixed Effects	✓	✓	✓	✓
Class Fixed Effects	✓	✓	✓	✓
Instructor Fixed Effects	✓	✓	✓	✓
Avg. dep. var.	2.5			
Avg. total hours on Canvas	13.7			
Avg. total Uber hours	145.4			

Note: The variable "Total Uber hours" denotes the total hours an Uber-student spent connected to the Uber platform throughout the course. "Total Canvas hours" refers to the sum of individual Uber-student's own Canvas hours throughout a given course. Each regression model includes individual and course fixed-effects. The sample excludes all terms that were meaningfully disrupted by the Covid-19 pandemic. Due to the inclusion of individual fixed effects, the number of observations that identify the parameters of interest is smaller when compared to the number of observations reported in Table 3. Standard errors are clustered at the course level. The model in Column (2) is estimated via 2SLS where "Total Uber hours" and "(Total Uber hours)^2 are instrumented with the average (across weeks) of average market level wages for Uber drivers who were eligible for the ASU-Uber program but did not enroll and its square. The model in Column (4) is estimated via 2SLS where "Total Canvas hours" and "(Total Canvas hours)^2 are instrumented with the sum (across weeks) of average Canvas hours for non-Uber peers in the course and its square. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

in labor market conditions (i.e., market hourly pay) could impact students' academic performance through a reduction in study hours. Combining the estimates from Tables 7 and 9, we find that a 10% increase in average hourly pay will only lead to a small decrease in course grade performance, roughly 0.04 grade points.[56]

In summary, the findings strongly suggest that flexible working and learning arrangements

[56] From Table 7, a 10% increase in average weekly earnings of peers is \$3.36, implying a reduction in weekly study hours by 0.0269 hours (i.e., \$3.36×-0.008). If we multiply this number by 7 (7 weeks is the length of a class), then the decrease in the total number of study hours for a given course is 0.1883. Finally, if we use the estimates from Table 9, jointly with 0.1883, we obtain the 0.04 point decrease in the course grade.

could substantially reduce the negative impact of working hours on academic performance, providing a suitable environment for many working students who intend to increase their skills.

10 Conclusion

This is the first study that quantifies how college activities and labor market conditions impact labor supply and effort exerted in college. Our findings indicate that frictions associated with performing working and learning activities simultaneously are small when workers participate in flexible (work and study) environments. In particular, we find that average college activities lead to an average short-run opportunity cost of only $41 per week. We also show that a 10% increase in average hourly pay decreases study time for the average Uber-student by 2%. The small economic size of these estimates is consistent with our findings that Uber-students take advantage of their flexible context by adjusting their driving behavior when school demand increases. Finally, we find negligible effects of working hours on academic performance or of studying hours on the quality of workplace performance, further suggesting that crowding-out effects do not seem relevant in this context.

To conclude, while we cannot provide a welfare analysis due to the lack of data on leisure or longer-term outcomes (such as graduation or subsequent labor market outcomes), our results are encouraging. Since low-income students are more likely to work to afford an increasingly expensive college education, flexible learning and working formats could help them overcome many of the usual barriers they face when pursuing a higher education degree. Similarly, our findings suggest this type of flexible working-flexible learning arrangement could also be convenient for many workers who aim to upgrade their skills.

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A Sample Restrictions

The primary way in which we restrict our data to construct our estimation sample is to limit the weeks included in our analysis. In particular, we drop all weeks between March 16, 2020 and January 4, 2021. The motivation for doing this is that the Covid-19 pandemic and related stay-at-home orders led to a massive disruption in Uber driver activity. We include the Spring term of 2021 in our analysis because, by that point, Uber driving had picked back up to somewhat normal levels, and a large share of our sample comes from that term. In addition to dropping these observations, we also exclude "Dynamic" courses from our estimating sample. These courses are often only one week long and make up a very small share of our Uber-student sample. Besides these restrictions, we do not place any other explicit filters on our estimating sample.

For our estimation of Equation (1) (i.e., event study), we also make additional sample restrictions. Specifically, we exclude individuals who appear to have "dropped out" during the course. As described previously, we determine likely dropouts based on their final course grades (e.g., incomplete or withdrawals) and their activity. Specifically, if a student receives a failing grade, an incomplete, or a withdrawal *and* has a spell of inactivity for at least the final three weeks of the course, we consider them a likely dropout. Though excluding these observations from our main results have little effect, they do matter in the estimation of our event study results since dropouts meaningfully attenuate our estimates in weeks after they drop out (since their driving hours are relatively high and study hours relatively low due to dropping out).[57]

B Decomposing the Cost of Effort

In this appendix, we provide the implementation details corresponding to the decomposition implemented in Section 7.

[57] Appendix Tables A14 and A15, present results where we re-estimate our main specifications but limit the sample by excluding likely dropouts.

Consider Equation (4) that relates the optimal work effort in a given week e^*_{ilt} to a set of structural parameters and observable data moments governing the costs and benefits of studying and working.[58] In order to map Equation (4) to the data, we re-express it as:

$$e^*_{ilt} = \frac{(\alpha-1)\lambda_{lc}\beta_1}{4\lambda_c\lambda_l - \lambda_{lc}^2} + \frac{(\alpha-1)\lambda_{lc}\beta_5\varsigma_t}{4\lambda_c\lambda_l - \lambda_{lc}^2} + \frac{2\alpha\lambda_c w_t}{4\lambda_c\lambda_l - \lambda_{lc}^2} + \frac{(\alpha-1)\lambda_{lc}\beta_3 Ab_i}{4\lambda_c\lambda_l - \lambda_{lc}^2}. \tag{9}$$

With Equation (9) in hand, we then estimate a slight variation of our primary specification in Equation (6) of the following form:

$$e_{ilt} = \gamma_0 + \gamma_1\varsigma_{it} + \gamma_2 w_{it} + \varphi_i + \vartheta_T + \varepsilon_{it}, \tag{10}$$

where e_{ilt} denotes hours worked, ς_{it} denotes course demand across all courses in week t, w_{it} is the market wage available to individual i in week t, and φ_i and ϑ_T are individual and term fixed-effects, respectively.[59] Given this setup, we assume that each of the estimands of Equation (10) corresponds to our structural parameters as follows:

$$\gamma_1 = \frac{(\alpha-1)\lambda_{lc}\beta_5}{4\lambda_c\lambda_l - \lambda_{lc}^2} \tag{11}$$

$$\gamma_2 = \frac{2\alpha\lambda_c}{4\lambda_c\lambda_l - \lambda_{lc}^2}. \tag{12}$$

A similar exercise for optimal study effort also yields a mapping from estimands of the estimating equation to the structural parameters. To be consistent with the analytical framework, we add study effort across all courses in which the student is enrolled in each period:

$$\sum_c^C e_{ict} = \pi_0 + \pi_1\varsigma_{it} + \pi_2 w_{it} + \varphi_i + \vartheta_T + \epsilon_{it},$$

[58] The marginal benefit of studying an extra hour is the marginal improvement in grades that an hour of studying generates (weighted by $(1-\alpha)$), and the marginal benefit of working is the market wage (weighted by α).

[59] As in our previous analysis we define ς_{it} as the average study hours of course peers.

where

$$\pi_1 = \frac{2(1-\alpha)\lambda_l \beta_5}{4\lambda_c \lambda_l - \lambda_{lc}^2} \tag{13}$$

$$\pi_2 = -\frac{\alpha \lambda_{lc}}{4\lambda_c \lambda_l - \lambda_{lc}^2}. \tag{14}$$

Though directly identifying any given structural parameter is not possible from Equations (11) - (14), we can use them jointly with the reduced-form estimates to recover the following ratios:[60]

$$-\frac{2\gamma_1}{\pi_1} = \frac{\lambda_{lc}}{\lambda_l} \tag{15}$$

$$-\frac{2\pi_2}{\gamma_2} = \frac{\lambda_{lc}}{\lambda_c}. \tag{16}$$

Finally, if we combine Eqs.(15)- (16) with the following expressions of the marginal costs of working (l) and learning (c) that are derived from our analytical framework:

$$MC_l = 2\lambda_l e_{ilt} + \lambda_{lc} e_{ict} \tag{17}$$

and

$$MC_c = 2\lambda_c e_{ict} + \lambda_{lc} e_{ilt}, \tag{18}$$

then, we can uncover the proportion of MC_l and MC_c (conditional on different levels of effort) that correspond to the direct cost of exerting each activity and of exerting both activities at the same time (i.e., complementarity costs).[61]

[60]The reduced-form coefficients (i.e., γ's and π's) are reported in Appendix Table A11. To be consistent with the fact that the first order conditions only hold at interior points, in this analysis we limit our estimating sample to individual weeks with strictly positive Canvas and Uber hours. Even though we have slightly altered our specification and our estimating sample, it is worth noting that the coefficient estimates from this specification are qualitatively and quantitatively similar to those estimated from our primary specifications and presented in Tables 6 and 7.

[61]The average study and work hours for the estimating sample in this exercise is somewhat higher than the overall sample. This is, in part, because we have dropped observations with zero hours. For reference, the average study hours for this sample is 3.38 hours per week (across all courses), and the average driving hours is 22.55.

C Appendix Tables

Table A1: Correlations of Canvas activity measures for Uber-students

	Active days	Logins	Clicks	Minutes online
Active days	1			
Logins	0.826^{***}	1		
Clicks	0.639^{***}	0.756^{***}	1	
Minutes online	0.568^{***}	0.715^{***}	0.847^{***}	1
Observations	71907			

Note: Table reports correlation coefficients across each metric of weekly Canvas activity. "Active days" corresponds to the number of days in the week with non-zero Canvas activity, "Logins" refer to the number of distinct times a student logged onto the course Canvas page, "Clicks" reflect the number of distinct clicks that were made on various course page links, and "Minutes online" refer to the number of minutes the student spent on the course Canvas page. *** $p < 0.05$, *** $p < 0.01$, *** $p < 0.001$

Table A2: Weekly Canvas activity by student group, re-weighted control group

	Uber-Students Active in Uber		Uber-Students Inactive in Uber		Class Peers	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Activity						
Days connected to Canvas per course	3.57	(2.304)	3.75	(2.274)	3.59	(2.241)
Clicks per course	76.02	(89.370)	79.06	(85.577)	69.14	(77.842)
Hours online per course	1.57	(2.116)	1.61	(2.097)	1.39	(1.820)
Outcomes						
Assignments submitted	1.97	(4.143)	1.99	(2.920)	2.03	(3.999)
Assignment share (%)	90.18	(27.599)	90.55	(26.809)	89.93	(27.767)
Point share (%)	79.39	(29.322)	80.13	(28.662)	79.49	(29.279)
Observations	43467		12197		125649	

Note: The "Class Peers" control group is re-weighted using coarsened exact matching on observables to be more similar to the Uber-student sample. All statistics reported in the table are at the weekly level. "Uber-Students: Active in Uber" denotes weeks in which the student shows positive driving hours and is enrolled in ASU classes. "Uber Students: Inactive in Uber" denotes weeks in which the student shows zero driving hours but is enrolled in ASU classes. "Class peers" correspond to students who are enrolled in the same classes as the Uber students. Assignment and point shares refer to the total number of assignments submitted and points earned relative to the number of assignments due and points possible, respectively.

Table A3: Student degree progress by enrollee type

	Uber-Students		Class Peers		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Cumulative GPA	2.62	(1.386)	2.94	(1.091)	-0.33^{***}
Credits to date	92.56	(54.110)	87.80	(46.490)	4.76^{***}
Observations	1540		64248		65788

Note: Means are reported for each variable measured at the most recent term in the data for each student. "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students enrolled in the same classes as the Uber students. "Cumulative GPA" refers to the student's cumulative grade point average at their most recent observed term and "Credits to date" denotes the total number of academic credits on a student's transcript including transfer credits. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A4: Course-level summary statistics, re-weighted control group

	Uber-Students		Class Peers	
	Mean	Std. Dev.	Mean	Std. Dev.
Activity				
Total hours on Canvas	14.63	(12.734)	13.00	(11.589)
Assignments submitted	18.38	(16.892)	19.04	(17.710)
Outcomes				
Passed course	0.76	(0.427)	0.78	(0.413)
Numeric course grade	2.49	(1.664)	2.55	(1.619)
Observations	6591		14527	

Note: "Uber-Students" denotes ASU students that participate in the ASU-Uber partnership. "Class Peers" corresponds to students that are enrolled in the same classes as the Uber students. The "Class Peers" group is re-weighted by coarsened exact matching on observables to be more similar to the sample of Uber-students.

Table A5: Correlations of Uber activity measures for enrolled Uber-students

	Total pay (100s)	Incentive pay (100s)	Tips (100s)	Completed trips	Hours online
Total pay (100s)	1				
Incentive pay (100s)	0.671^{***}	1			
Tips (100s)	0.517^{***}	0.296^{***}	1		
Completed trips	0.887^{***}	0.580^{***}	0.534^{***}	1	
Hours online	0.840^{***}	0.408^{***}	0.499^{***}	0.833^{***}	1
Observations			22999		

Note: Table reports correlation coefficients across each metric of weekly Uber activity."Total pay" corresponds to the driver's total weekly earnings from Uber, "Incentive pay" refers to pay received due to specific incentive programs (e.g., completing a target number of trips), "Tips" reflect the weekly earnings received in formal passenger tips, and "Completed trips" and "Hours online" denote the total number of trips completed and hours spent on the Uber application, respectively. *** $p < 0.05$, *** $p < 0.01$, *** $p < 0.001$

Table A6: Determinants of work effort

	(1) Work Hours	(2) Work Hours	(3) Work Hours	(4) Completed Trips	(5) Completed Trips	(6) Completed Trips
Total assignments across all c	-0.054**	-0.053**	-0.024	-0.083	-0.082	-0.039
	(0.027)	(0.027)	(0.027)	(0.062)	(0.062)	(0.066)
Market level active hourly pay, currently elig.	0.118**	0.128**		0.342***	0.372***	
	(0.051)	(0.051)		(0.112)	(0.113)	
Individual Fixed Effects	✓	✓	✓	✓	✓	✓
Course Bundle Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed effects	✓	✓	✓	✓	✓	✓
Weather controls		✓			✓	
City-Week FE			✓			✓
Mean dep. var.	18.24	18.21	18.39	36.52	36.48	36.78
Market level active hourly pay, peers	33.62	33.61		33.6	33.6	
Mean assignments	4.24	4.24	2.46	4.24	4.24	2.46
First-stage F-stat	87.08	86.97	126.07	87.08	86.97	126.07

Note: Columns (1) to (3) include as dependent variable weekly work hours, while columns (4) to (6) include completed trips. The variable "Total assignments across all c, peers" denotes the sum of an individual's graded assignments across all classes in a week. Total assignments are instrumented with the sum of average assignments graded for peer students. The variable "Market level active hourly pay, currently elig." denotes the average hourly pay of drivers (currently eligible) in a given week. Specifications include multiple sets of fixed effects. Course bundle fixed effects denote the set of courses taken in a given term. Weather controls account for temperatures and rains/snow. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A7: Robustness: Determinants of work effort

	(1) Work Hours	(2) Work Hours
Sum avg. study hours all c, peers	-0.668***	-0.551***
	(0.097)	(0.111)
Market level active hourly pay, currently elig.	0.217***	0.338***
	(0.051)	(0.071)
Observations	21572	22141
Individual Fixed Effects	✓	
Course Bundle Fixed Effects	✓	
Month-Year Fixed effects	✓	✓
Weather controls	✓	✓
Leads and lags of indep. variables	✓	✓
Mean dep. var.	17.75	17.78
Mean avg. study hours in c, peers	2.65	2.66
Market level active hourly pay, peers	33.1	33.7

Note: The variable "Sum avg. study hours all c, peers" is a proxy for coursework that denotes the sum of average Canvas hours of non-Uber students in each course c in which the Uber-student is enrolled. The variable "Market level active hourly pay, currently elig." denotes the average hourly pay of drivers (currently eligible) in a given week. The specification includes multiple sets of fixed effects. Course bundle fixed effects denote the set of courses taken in a given term. Weather controls account for temperatures and rains/snow. A one week lead and lag of each of the independent variables of interest are also included as controls. Column (2) does not include individual and course bundle fixed effects, given that models with lagged dependent variables can be biased when including fixed effects. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A8: Robustness: Determinants of study effort

	Study Hours in c	Study Hours in c
Avg. study hours in c, peers	1.152***	1.152***
	(0.032)	(0.030)
Sum avg. study hours in $-c$, peers	0.009	0.023*
	(0.011)	(0.012)
Market level active hourly pay, currently elig.	-0.009**	-0.008**
	(0.004)	(0.004)
Observations	41989	41993
Individual Fixed Effects	✓	
Classroom Fixed Effects	✓	✓
Month-Year Fixed Effects	✓	✓
Leads and lags of indep. variables	✓	✓

Note: The variable "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in c. "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c in which the student was enrolled. The variable "Market level active hourly pay, currently elig." denotes the average hourly pay of drivers (currently eligible) in a given week. The specification includes multiple sets of fixed effects. Weather controls account for temperatures and rain/snow. A one-week lead and lag of each of the independent variables of interest are also included as controls. Standard errors are clustered at the class level.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A9: Determinants of study effort (clicks and logins)

	Weekly clicks	Weekly logins	Weekly clicks	Weekly logins
Avg. study hours in c, peer	36.868***	2.105***		
	(5.580)	(0.596)		
Sum of avg. study hours in $-c$, peers	-0.226	-0.048		
	(0.373)	(0.038)		
Assignments graded in c			2.036***	0.220***
			(0.464)	(0.048)
Sum of assignments graded in $-c$			-0.531***	-0.036**
			(0.155)	(0.015)
Market level active hourly pay, currently elig.	-0.904***	-0.026	-1.616***	-0.068***
	(0.196)	(0.019)	(0.204)	(0.017)
Obs.	55293	55293	55293	55293
Individual Fixed Effects	✓	✓	✓	✓
Classroom Fixed Effects	✓	✓	✓	✓
Month-Year Fixed effects	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Mean dep. var.	76.79	9.01	76.79	9.01
Market level active hourly pay, peers	33.57	33.57	33.57	33.57
Avg. study hours in c, peers	1.28	1.28	-	-
Sum avg. study hours in $-c$, peers	1.55	1.55	-	-
Assignments graded in c	-	-	2.21	2.21
Sum assignments graded in $-c$	-	-	2.78	2.78
Elasticity w.r.t. peer coursework	0.615	0.286	0.059	0.054
Elasticity w.r.t. peer earnings	-0.395	-0.097	-0.508	-0.253

Note: The dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. "Assignments graded in c" and "Sum of assignments graded in $-c$" denote the number of assignments graded in course, c, and all other courses, $-c$ for a student in a given week. The results in Columns (3) and (4) are from a 2SLS specification where "Assignments graded in c" and " Sum of assignments graded in $-c$" are instrumented with the average assignments graded by non-Uber peers in c and $-c$, respectively."Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Specifications include multiple sets of fixed effects. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. Elasticities are calculated by multiplying the relevant coefficient estimate by the ratio of mean course work or market level hourly earnings to the mean of the dependent variable. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A10: Heterogeneity in the determinants of study and work hours

	Full-time driver (1)	STEM (2)	Female (3)	High-need (4)	High Incoming GPA (5)
Panel A: Work hours					
Market level active hourly pay, currently elig.	0.124**	0.138**	0.177***	0.134	0.097
	(0.057)	(0.063)	(0.057)	(0.083)	(0.071)
Market level active hourly pay, currently elig. × var. in top row	0.096	0.090	-0.052	0.046	0.091
	(0.112)	(0.115)	(0.109)	(0.102)	(0.106)
Sum avg. study hours all c, peers	-0.381***	-0.360***	-0.497***	-0.554***	-0.465***
	(0.090)	(0.092)	(0.094)	(0.132)	(0.115)
Sum avg. study hours all c, peers × var. in top row	-0.237*	-0.285**	0.166	0.079	0.027
	(0.137)	(0.136)	(0.157)	(0.144)	(0.134)
Observations	27404	26636	26690	27388	23902
Panel B: Study hours					
Market level active hourly pay, currently elig.	-0.010**	-0.007	-0.007*	-0.011*	-0.007
	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)
Market level active hourly pay, currently elig. × var. in top row	0.006	-0.001	-0.015	0.003	-0.003
	(0.006)	(0.006)	(0.010)	(0.007)	(0.006)
Avg. study hours in c, peers	1.041***	1.074***	1.077***	0.978***	1.023***
	(0.076)	(0.042)	(0.061)	(0.166)	(0.063)
Avg. study hours in c, peers × var. in top row	0.207*	0.156**	0.315	0.205	0.107*
	(0.124)	(0.063)	(0.243)	(0.198)	(0.055)
Sum of avg. study hours in $-c$, peers	-0.006	0.002	-0.003	0.004	-0.019**
	(0.008)	(0.008)	(0.008)	(0.018)	(0.008)
Sum of avg. study hours in $-c$, peers × var. in top row	-0.008	-0.027**	-0.045	-0.017	0.009
	(0.013)	(0.013)	(0.033)	(0.022)	(0.012)
Observations	55293	53731	53975	55266	48263

Note: For Panel A—the dependent variable in each column is hours working on the Uber platform. "Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership but not enrolled. "Sum of avg. study hours across all c, peers" denotes the sum of the average hours per week that peers spent on Canvas across all courses. For Panel B—the dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. All specifications include multiple sets of fixed effects, second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. In Panel A, standard errors are clustered at the individual level. In Panel B, standard errors are clustered at the class level.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A11: Intermediate coefficient estimates and model parameters

	(1) e^*_{ilt}	(2) e^*_{ict}
ς_{it}	-0.718***	1.311***
	(0.079)	(0.062)
w_{it}	0.064*	-0.012*
	(0.038)	(0.007)
Obs.	19050	19050
Implied λ_{lc}/λ_l	1.096	
Implied λ_{lc}/λ_c	0.381	

Note: The dependent variable Column (1) is weekly driving hours for driver i in week t and the dependent variable in Column (2) is total Canvas hours across all courses for i in t. ς_{it} is a proxy for coursework that denotes weekly Canvas hours of non-Uber peers across all of student i's courses. w_{it} denotes the average active hourly pay in a given week for drivers who are currently eligible for the ASU-Uber partnership, but not enrolled in the same city as i. Estimation sample is restricted to person-weeks with strictly positive Canvas and Uber hours. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A12: The effect of work and study effort on course completion

	(1) Completion	(2) Completion (IV)	(3) Completion	(4) Completion (IV)
Total Uber hours	0.000	-0.001		
	(0.000)	(0.014)		
(Total Uber hours)^2	0.000	0.000		
	(0.000)	(0.000)		
Total Canvas hours			0.031***	0.072***
			(0.003)	(0.010)
(Total Canvas hours)^2			-0.000***	-0.001***
			(0.000)	(0.000)
Obs.	4900	4900	4900	4900
Adjusted R^2	0.38	.	.52	.
Individual Fixed Effects	✓	✓	✓	✓
Class Fixed Effects	✓	✓	✓	✓
Instructor Fixed Effects	✓	✓	✓	✓
Avg. dep. var.	.81			
Avg. total hours on Canvas	13.7			
Avg. total Uber hours	145.4			

Note: The variable “Total Uber hours” denotes the total hours an Uber-student spent connected to the Uber platform throughout the course. “Total Canvas hours” refers to the sum of individual Uber-student’s own Canvas hours throughout a given course. Each regression model includes individual and course fixed-effects. The sample excludes all terms that were meaningfully disrupted by the Covid-19 pandemic. Due to the inclusion of individual fixed effects, the number of observations that identify the parameters of interest is smaller when compared to the number of observations reported in Table 3. Standard errors are clustered at the course level. The model in Column (2) is estimated via 2SLS where “Total Uber hours” and “(Total Uber hours)^2 are instrumented with the average (across weeks) of average market level wages for Uber drivers who were eligible for the ASU-Uber program but did not enroll and its square. The model in Column (4) is estimated via 2SLS where “Total Canvas hours” and “(Total Canvas hours)^2 are instrumented with the sum (across weeks) of average Canvas hours for non-Uber peers in the course and its square. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A13: The effect of work and study effort on course pass rate

	(1) Completion	(2) Completion (IV)	(3) Completion	(4) Completion (IV)
Total Uber hours	0.000	-0.010		
	(0.000)	(0.035)		
(Total Uber hours)^2	0.000	0.000		
	(0.000)	(0.000)		
Total Canvas hours			0.033***	0.067***
			(0.002)	(0.009)
(Total Canvas hours)^2			-0.000***	-0.001***
			(0.000)	(0.000)
Obs.	4900	4900	4900	4900
Adjusted R^2	0.45	.	.58	.
Individual Fixed Effects	✓	✓	✓	✓
Class Fixed Effects	✓	✓	✓	✓
Instructor Fixed Effects	✓	✓	✓	✓
Avg. dep. var.	.75			
Avg. total hours on Canvas	13.7			
Avg. total Uber hours	145.4			

Note: The variable "Total Uber hours" denotes the total hours an Uber-student spent connected to the Uber platform throughout the course. "Total Canvas hours" refers to the sum of individual Uber-student's own Canvas hours throughout a given course. Each regression model includes individual and course fixed-effects. The sample excludes all terms that were meaningfully disrupted by the Covid-19 pandemic. Due to the inclusion of individual fixed effects, the number of observations that identify the parameters of interest is smaller when compared to the number of observations reported in Table 3. Standard errors are clustered at the course level. The model in Column (2) is estimated via 2SLS where "Total Uber hours" and "(Total Uber hours)^2 are instrumented with the average (across weeks) of average market level wages for Uber drivers who were eligible for the ASU-Uber program but did not enroll and its square. The model in Column (4) is estimated via 2SLS where "Total Canvas hours" and "(Total Canvas hours)^2 are instrumented with the sum (across weeks) of average Canvas hours for non-Uber peers in the course and its square. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A14: Determinants of work effort, excluding likely dropouts

	(1) Work Hours	(2) Work Hours	(3) Work Hours	(4) Completed Trips	(5) Completed Trips	(6) Completed Trips
Sum of avg. study hours across all c, peers	-0.686***	-0.683***	-0.677***	-1.286***	-1.280***	-1.337***
	(0.073)	(0.073)	(0.101)	(0.147)	(0.147)	(0.206)
Market level active hourly pay, currently elig.	0.108**	0.115**		0.301***	0.326***	
	(0.051)	(0.051)		(0.112)	(0.113)	
Obs.	25972	25907	24777	25972	25907	24777
Individual Fixed Effects	✓	✓	✓	✓	✓	✓
Course Bundle Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed effects	✓	✓	✓	✓	✓	✓
Weather controls		✓			✓	
City-Week FE			✓			✓
Mean dep. var.	18.01	17.98	18.19	36.09	36.03	36.38
Market level active hourly pay, peers	33.64	33.63		33.64	33.63	
Sum avg. study hours all c, peers	2.48	2.48	2.49	2.48	2.48	2.49
Mean hourly earnings	19.1	19.1	19.23	19.1	19.1	19.23
Mean pay-per-trip	9.76	9.76	9.83	9.76	9.76	9.83

Note: Columns (1) to (3) include as dependent variable weekly work hours, while columns (4) to (6) include completed trips. The variable "Sum of avg. study hours across all c, peers" denotes the sum of the average hours across courses that peers spent on Canvas per week. The variable "Market level active hourly pay, currently elig." denotes the average hourly pay of drivers (currently eligible) in a given week. Likely dropouts are excluded from the estimating sample. Additional details on how we identify likely dropouts are provided in Appendix A. Specifications include multiple sets of fixed effects. Course bundle fixed effects denote the set of courses taken in a given term. Weather controls account for temperatures and rains/snow. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

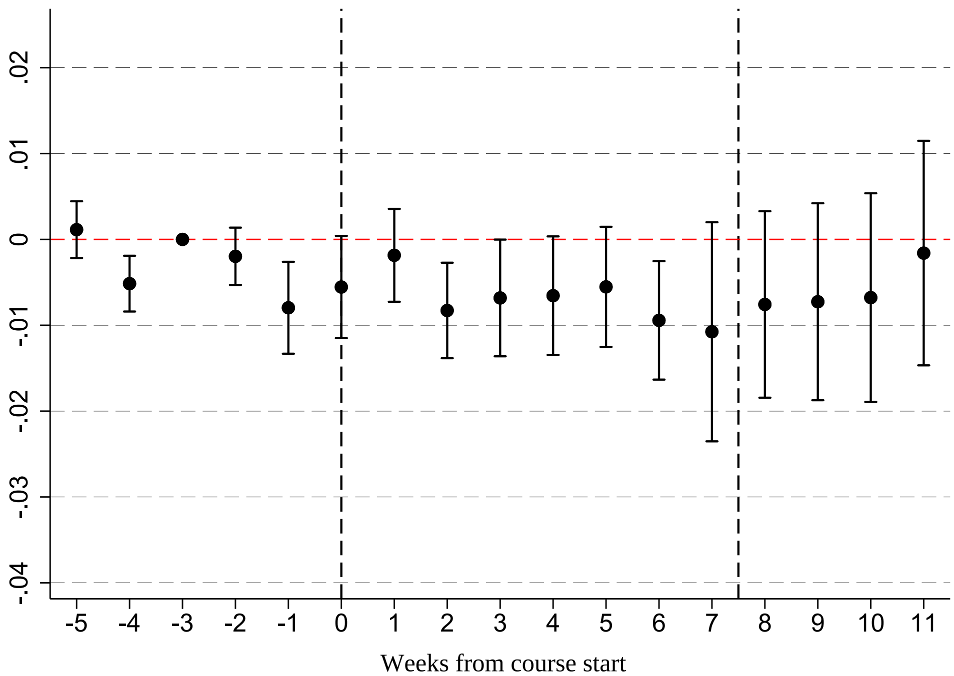
Table A15: Determinants of study effort, excluding likely dropouts

	Study Hours in c (1)	Study Hours in c (2)
Avg. study hours in c, peers	1.206***	-
	(0.027)	
Sum avg. study hours in $-c$, peers	-0.011*	-
	(0.006)	
Assignments in c	-	0.045***
		(0.015)
Sum assignments in $-c$	-	-0.012**
		(0.005)
Market level active hourly pay, peers	-0.005	-0.028***
	(0.003)	(0.004)
Observations	51385	51385
Individual Fixed Effects	✓	✓
Classroom Fixed Effects	✓	✓
Month-Year Fixed effects	✓	✓
Weather controls	✓	✓
Mean dep. var.	1.7	1.7
Avg. study hours in c, peers	1.28	-
Sum avg. study hours in $-c$, peers	1.56	-
Assignments in c	-	2.21
Sum assignments in $-c$	-	2.78
Market level active hourly pay, peers	33.58	33.57

Note: The dependent variable in each column is weekly study hours in course c. “Avg. study hours in c, peers” is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable “Sum of avg. study hours in $-c$, peers” denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. “Assignments in c” and “Sum of assignments in $-c$” denote the number of assignments graded in course, c, and all other courses, $-c$ for a student in a given week. The results in Column (2) are from a 2SLS specification where “Assignments in c” and “ Sum of assignments in $-c$” are instrumented with the average assignments submitted by non-Uber peers in c and $-c$, respectively.“Market level active hourly pay, currently elig.” denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Likely dropouts are excluded from the estimating sample. Additional details on how we identify likely dropouts are provided in Appendix A. Specifications include multiple sets of fixed effects. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. Standard errors are clustered at the class level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

D Appendix Figures

Figure A1: Event study results for share of pay coming from tips during eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is the share of weekly earnings coming from tips and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

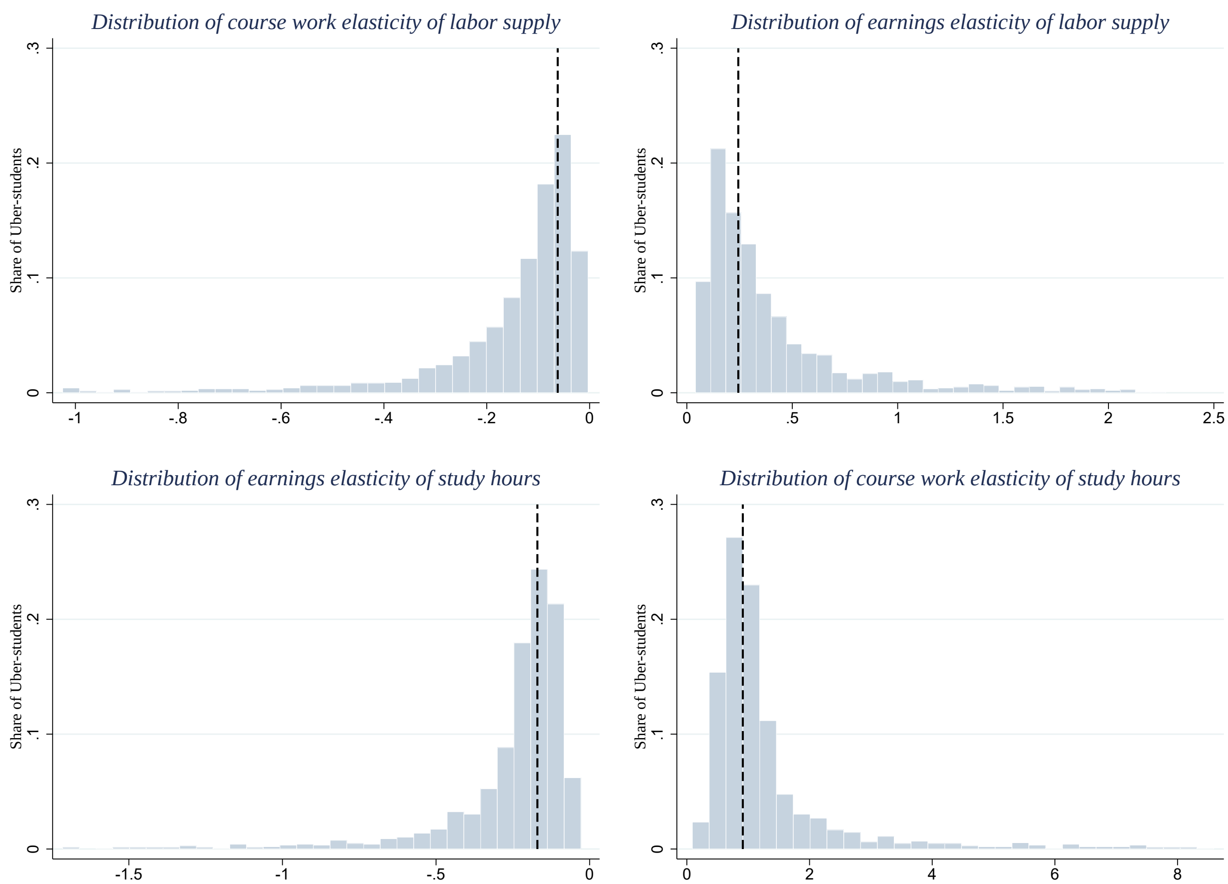
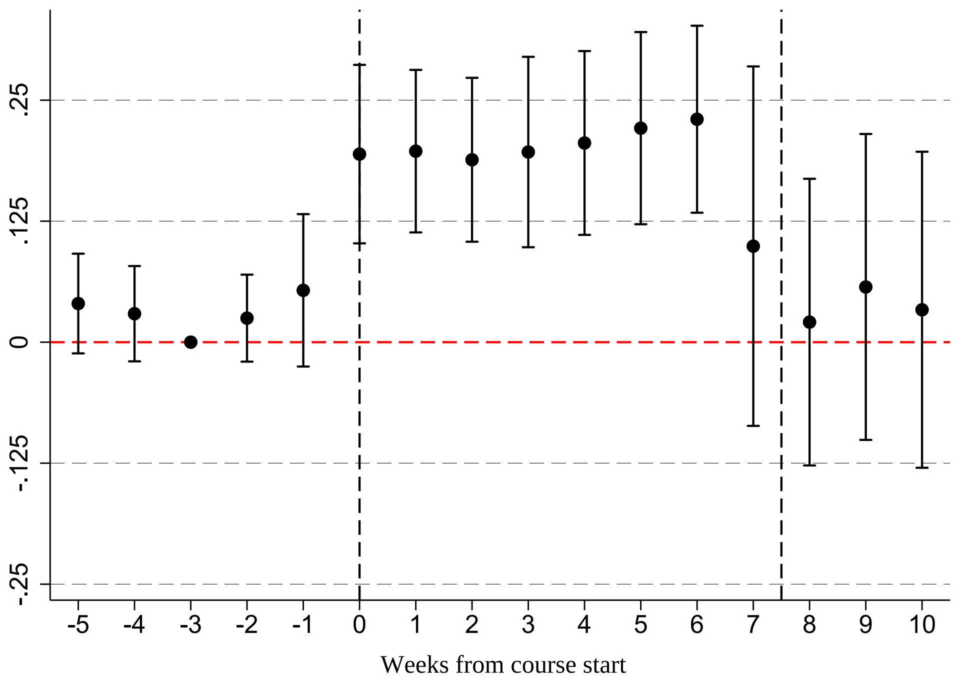


Figure A2: Distribution of elasticities using individual-level means of relevant variables (i.e., average market-level earnings, peer course hours, own driving and study hours while enrolled at ASU).

Figure A3: Event study results for flexibility on weekend nights during eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is the dissimilarity index for share of driving hours allocated in Friday and Saturday afternoons and nights (i.e., 12:00PM-12:00AM) and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course.